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MODEL SELECTION FOR THE DYNAMICS OF SOUTHERN AFRICAN HAKE RESOURCES

by

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ABSTRACT

One hundred and six different surplus production model-estimation procedure combinations which could potentially form the basis for management of the hake resources in the ICSEAF Convention Area (including the three currently in use), are compared with regard to the accuracy and precision of their estimates of management related quantities, using Linhart and Zucchini's (1986) "operating model" concept and computer simulation. Ten different variance estimation procedures are compared with respect to their accuracy and precision in providing coefficients of variation and standard errors for these management variables.

The estimation procedures in current use by ICSEAF produce parameter and variable estimates with substantial positive bias when their performance is evaluated using Butterworth's (1988a) age-structured operating model. Urgent adaptations to (or rejection of) these procedures are required to avoid marked depletion of the hake resources in the short term, as quotas appear to be well above those corresponding to the $f_{0.1}$ strategy, which is the current basis for management of these fisheries. In particular, it is proposed that all procedures based on Gulland's (1961) regression method for estimation of the control effort level ($E_{0.1}$) be rejected.

Incorporation of auxiliary information improves the accuracy and precision of management variable estimates; both observation and process error estimators are unable to estimate the model parameters from the available data with reasonable precision unless an assumption about the biomass at the start of exploitation is made [for process error estimators this involves making an assumption about the relationship between the cpue at the start of exploitation and other model parameters]. This information is useful for the circumstances investigated here, essentially because the Butterworth age-structured operating model (which is intended to be a close representation of the hake resource in ICSEAF Divisions 1.3 + 1.4) assumes that the stock was at its carrying capacity level at the start of exploitation. Data contrast and the length of the available data series are the most critical factors in determining the number of model parameters which can be estimated reliably, while serial correlation (caused by the same model estimation procedure being used to assess the stock and to set quotas) is shown to have no substantial effect on variable estimation. Pre-smoothing of cpue data does not improve the accuracy of parameter estimates substantially.

The one hundred and six model-estimation procedure combinations were reduced to sixteen by excluding those which gave substantially biased estimates. The remaining sixteen combinations were tested for robustness by varying the parameters of the operating model in seventeen different ways. Six of these sixteen combinations were selected by considering the average deviation of the estimates of management variables from their "true" values over the seventeen robustness tests. Of these six, the Schaefer form of the Butterworth-

Andrew model, using the Ludwig-Walters-Cooke Total Least Squares estimator (under the assumption of equal process and observation error variance), performs best according to this criterion, with average deviations of typically 20% in estimating $f_{0.1}$ strategy quotas. In general, model-estimation procedure combinations based on the Schaefer form of the surplus production function performed better than those based on the Fox form.

The (conditioned) parametric bootstrap method is recommended for use by ICSEAF for variance estimation, and the bias-corrected percentile method for confidence interval estimation. Although the variance estimates produced are negatively biased, the size of this bias is roughly comparable for different model estimation procedures (given a fixed operating model error structure). As a result, use of the inverse of such variance estimates to weight the results produced by different model estimation procedures would not be expected to introduce any substantial bias. However, use of the jack-knife variance estimator for this purpose is questioned, as the biases obtained using this method vary considerably depending on the model estimation procedure used.

Possible further extensions to this work are discussed; these include increasing the realism of the Butterworth age-structured operating model in order to determine more accurately the robustness of the model estimation procedures to a complex underlying situation. Techniques for assessing estimation procedures based on data other than catch and effort only, are also discussed.

CONTENTS

1 INTRODUCTION

1.1 Rationale for study

As an initial basis of management recommendations for the Cape hake stocks off the southwest African coast, the Scientific Advisory Council (SAC) of the International Commission for the South East Atlantic Fisheries (ICSEAF) at present uses an arithmetic average of the results of three "dynamic" production model estimation procedures for estimating $f_{0.1}$ strategy quotas. These three estimation procedures [Babayan *et al.* (1985,1986,1987,1988), Lleonart *et al.* (1985a) and Butterworth and Andrew (1984)] are all based on catch and effort data only. (The $f_{0.1}$ and f_{MSY} strategies are described in Chapter 4.)

This process gives rise to a number of potential problems. Butterworth and Andrew (1987a) note that the three procedures employed yield markedly different and hence confusing results. The justification for a simple arithmetic average is also questionable, as it is unlikely that all three model estimation procedures are equally reliable. Butterworth and Andrew (*op. cit.*), for example, show that the procedures proposed by Babayan *et al.* (1985,1986,1987,1988), which fail to take dynamics into account fully in estimating control effort levels, are unlikely to be unbiased (i.e. on average, correct), in contrast to other procedures which do so [such as the procedure suggested by Butterworth and Andrew (1984)]. Further, comparison of the biomasses assessed from catch-age-structure data using Virtual Population Analysis (VPA) with those calculated using one of the forms of such a fully dynamic procedure [the Butterworth-Andrew (Fox form) $y_1 = K$ observation error estimator

(Butterworth and Andrew 1984)] indicates markedly different values and trends (Butterworth *et al.* 1986a), suggesting that production-model-type estimators may not be able to reproduce the dynamics of an age-structured population at all accurately. The possibility exists, nevertheless, that the large number of other production-model-type estimation procedures available may include some which are superior to those currently in use, and which therefore warrant closer inspection.

In order to resolve these problems, it is desirable for all the known combinations of models and estimation procedures which have been suggested in the literature to be compared objectively. Butterworth (1988a) proposes that the performance of each approach, as measured by the accuracy (size of variance) and precision (size of variance) of the management variable estimates it produces, be tested by simulation using the "operating model" concept advocated by Linhart and Zucchini (1986). (This concept is described in detail in Chapter 7). This suggestion is implemented here by comparing the estimation procedures in terms of the bias and discrepancy (some measure of the difference between the estimated and actual value of a management variable) of their estimates of $Q_{0.1}$ (the quota under an $f_{0.1}$ strategy), the corresponding effort level ($E_{0.1}$), maximum sustainable yield (MSY), the f_{MSY} quota (Q_{MSY}) and the corresponding equilibrium effort (E_{MSY}), for a scenario closely resembling that of the hake stock in Divisions 1.3 + 1.4 of the ICSEAF Convention Area. The estimates of bias are considered first (for elimination of obviously substantially biased procedures), and subsequently the procedures are selected on the basis of minimum estimated expected discrepancy (this incorporates a measure of the degree of variability of the different estimators). The "best" model-estimation procedure combinations are thus selected by considering the trade-off between :

(a) their representation of the basic causal factors underlying the stock dynamics,

(b) their ability to provide accurate (low bias) and precise (low variance) estimates of management variables and

(c) their robustness to variation of the values of the parameters of the underlying operating model.

It should be noted that only the model-estimation procedure combinations themselves are considered here, and not possible alternative harvesting strategies. Although it is the success of each combination in estimating $f_{0.1}$ and f_{MSY} quotas and their associated equilibrium effort levels which is tested in the analyses that follow, any other well-defined harvesting strategy could be investigated similarly (Butterworth 1988a). For example, in the case of whale management, the performance of various combinations of a harvesting algorithm, a model and an estimation procedure have been assessed (Punt and Butterworth 1988). Computer time restrictions precluded the testing of a large number of harvesting algorithm-model estimation procedure combinations in this study, however; further, comparison of such combinations would require the values of economic parameters for measures of performance, and these are not readily available. Instead, attention has been focused on the $f_{0.1}$ harvesting strategy (and consequently the estimation of $Q_{0.1}$, in particular), as this is the strategy currently used by ICSEAF (see also discussion in Butterworth 1988a).

Butterworth (1988a) has suggested that instead of using an arithmetic average to pool $Q_{0.1}$ estimates from different models, a weighted average should be used in order to take into account estimate precision. The weighting scheme proposed by Butterworth (1988a) requires that an estimate of the variance, or equivalently the coefficient of variation (c.v.) [the ratio of the standard error (s.e.) of an estimate to the estimate itself], be obtained for $Q_{0.1}$. The ICSEAF SAC have subsequently agreed to adopt such an approach. Butterworth and Andrew (*op. cit.*) suggest the use of the Jack-knife and (Conditioned) Parametric (Monte-Carlo) Bootstrap methods of variance estimation (see Chapter 6 for a discussion of these), but fail to provide evidence that these methods are able to estimate the c.v.'s with sufficient accuracy (i.e. with small bias) or precision (i.e. with low variance). The reliability of ten variance estimation procedures is compared here with respect to :

(a) the accuracy of the c.v. and s.e. estimates produced (ideally these should be unbiased or consistently biased, so that the suggested procedure of pooling using inverse variance weighting is not in itself a biased procedure), and

(b) the variance of the c.v. and s.e. estimates (which should be small, reflecting precise estimation).

Owing to the computer time restrictions and the nature of the computations performed, some inconsistencies [particularly in the selection of model-estimation procedure combinations for variance estimation procedure testing and in the tests for serial correlation (see Chapter 6 for details)] have occurred in the logical sequence of results presented in this thesis. These have been caused primarily by new model estimation procedures [such as those of Ludwig *et al.* (1988)] becoming known only after a substantial number of computations had already been performed. Some of these procedures deserve and will in due course receive further investigation, but this was unfortunately not possible within the time limits available for this presentation.

1.2 Terminology

For convenience of expression, the term "management variable" will be used to mean any quantity estimated by a model estimation procedure [such as the maximum sustainable yield (MSY) or the $f_{0.1}$ strategy quota for the coming year, $Q_{0.1}(n+1)$], even though some of these quantities (such as MSY) are not variables, strictly speaking, but parameters. (Details of other differences that arise out of this distinction can be found in Chapter 7). For notational simplicity, the $f_{0.1}$ strategy quota for the forthcoming year, $Q_{0.1}(n+1)$, is denoted by $Q_{0.1}$.

Although various interpretations of the term "overexploited" exist (see Chapter 4), it is used here in the sense of biological overexploitation, i.e. to indicate that the current biomass is below that which corresponds to the production of maximum sustainable yield.

In order to reduce the confusion resulting from the paucity of suitable synonyms for the word "estimate", the term "model estimation procedure" is used to indicate the combination of a model and the method employed for estimating its parameters (and thus the management variables). [The "method" referred to here embodies an assumption about the error structure of the model and the specification of a minimisation criterion to be used in the fitting process (see Section 3.4).] When the meaning is clear, this combination is referred to as an "estimation procedure", omitting the word "model". The term "variance estimation procedure" is used to indicate a method for the estimation of some measure of precision (such as the variance, s.e. or c.v.) of a management variable. Variance estimation procedures are discussed in detail in Chapter 6.

The "error due to approximation" (Linhart and Zucchini 1986) refers to the "difference" between the model underlying the model estimation procedure and the true underlying dynamics of the fishery (which includes both the population dynamics of the resource and its response to the catching process). In certain circumstances, this error is equivalent to bias - the difference between the expected estimate and the true value. The "error due to estimation" (Linhart and Zucchini *op. cit.*), on the other hand, refers primarily to the variance that arises because the model estimation procedure is in practice applied to a finite-sized sample for estimation of the model parameters (although bias, when a function of sample size, can also contribute to this type of error). Both of these terms are illustrated by an example in Chapter 7.

In this thesis, the word "significant" is used only to indicate results which are statistically significant at the 5% level.

1.3 Overview of thesis

The balance of this Chapter deals briefly with the development of the Cape hake fisheries and the management measures implemented since the foundation of ICSEAF in 1972 in an attempt to halt the declining trends in the various stock biomasses. The major demographic features pertinent to a generalised model of the Cape hake stocks are outlined in Chapter 2. Chapter 3 details the theory underlying those production model estimation procedures which utilise catch-effort data only. Specific details of the methods used for estimating the parameters of a model, some of the major problems involved in the use of production model estimation procedures, and the data sets available are described.

Chapter 4 discusses fishery management methods which involve restriction either of catches or of fishing effort. Several alternatives to the $f_{0.1}$ strategy, *viz.* the use of economic reference points, the $MAC_{0.1}$ strategy and probing strategies, which could feasibly be used by ICSEAF for management of the hake stocks, are also discussed briefly. The derivation of the estimation procedures from their underlying mathematical models is described in Chapter 5, while Chapter 6 deals with methods of estimating the variance (or standard error) of management variable estimates.

Chapter 7 explains the "operating model" method of model selection (Linhart and Zucchini 1986) in the context of this study. The Butterworth age-structured operating model (Butterworth 1988a) is used here for this purpose. Chapter 8 contains a review of some of the techniques employed to date in the scientific literature for the evaluation of production model estimation procedures, with particular reference to those pertinent to management of the Cape hake resources.

Results and associated discussion of the model selection calculations appear in Chapters 9 and 10 respectively, together with extensions made to the testing procedure of Chapter 7 which were necessitated by initial findings. Chapter 11 discusses possibilities for future research by outlining further methods of extending the testing procedure which involve improving the realism of the Butterworth age-structured operating model, as well as suggesting methods of assessing the performance of procedures which use data other than catch and effort. In Chapter 12 the most important conclusions drawn from this study are summarised.

1.4 Historical background to the hake fishery

The Cape hake fishery was established before the turn of the century and has since become the most important bottom trawl fishery off southwestern Africa. Between the years 1958 and 1965, hake constituted an average of 65% by landed mass of all demersal species caught by the local industry. The fishery is the largest hake fishery in the world, with Cape hake contributing, for example, 33% in 1965, 41% in 1973 and 39% in 1977 of the total world hake catch.

Catches were initially low, an annual haul of 10 000 metric tons being recorded for the first time only in 1932, but increased steadily until 1954, by which time the annual catch had reached 100 000 metric tons. In 1962 foreign vessels joined the fishery and the fishing grounds expanded from the Cape Peninsula and Agulhas Bank area to cover virtually the entire continental shelf from the northern boundary of Namibia (South West Africa) to East London (see Fig. 1.1). At first the fishery concentrated on areas of high abundance, only extending its range later as stock densities decreased. A summary of the catches made by each nation for the period 1981 to 1986 is given in Table 1.1.

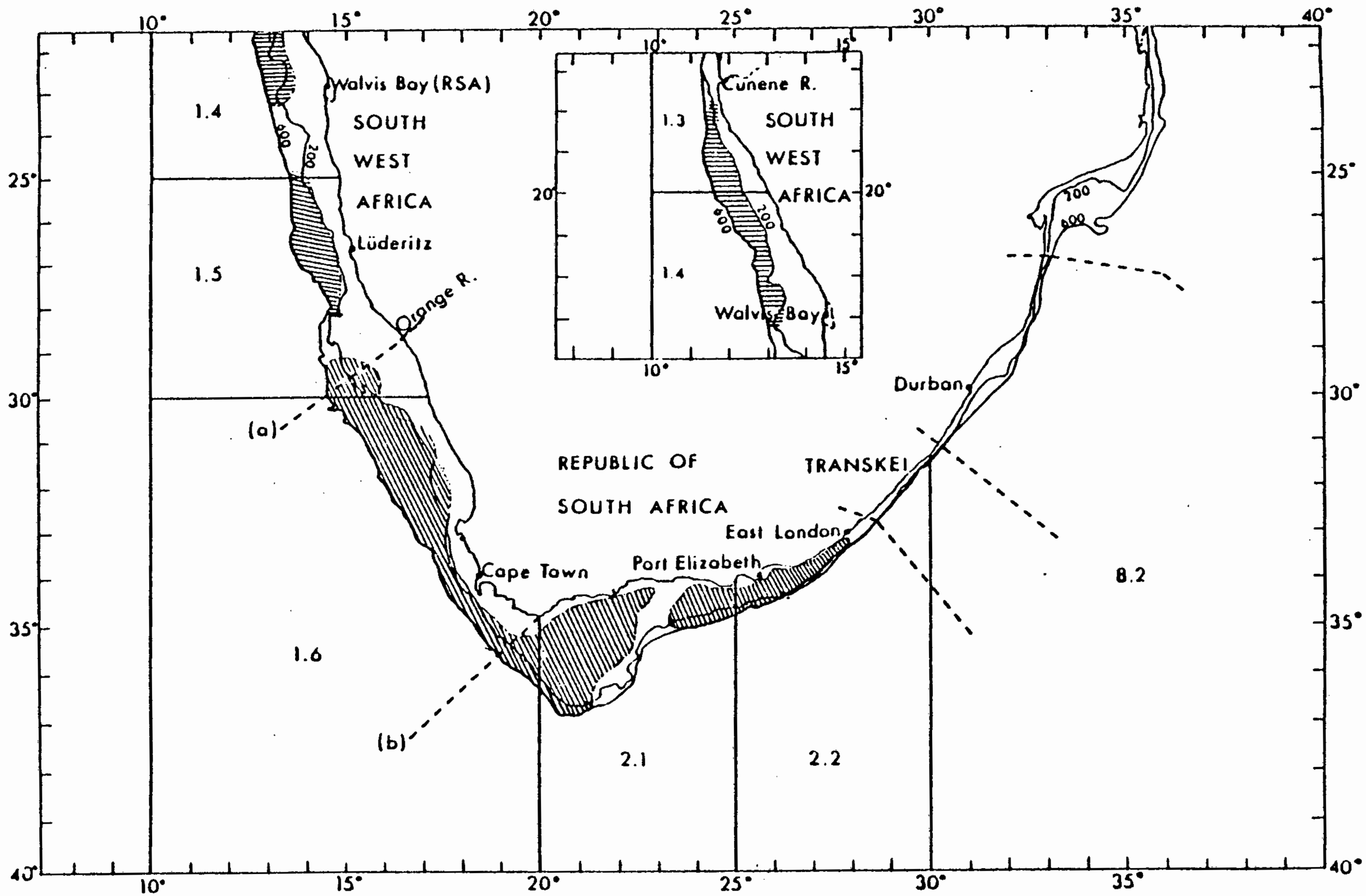


Figure 1.1: The major Cape hake trawling grounds and the ICSEAF Division boundaries off southern Africa (based on unpublished SFRI and ICSEAF statistics). The boundaries marked (a) and (b) refer respectively to the boundaries of Division 1.6 and of the adjoining Divisions which have been specified for domestic (South African) purposes [after Andrew and Butterworth (1987a)].

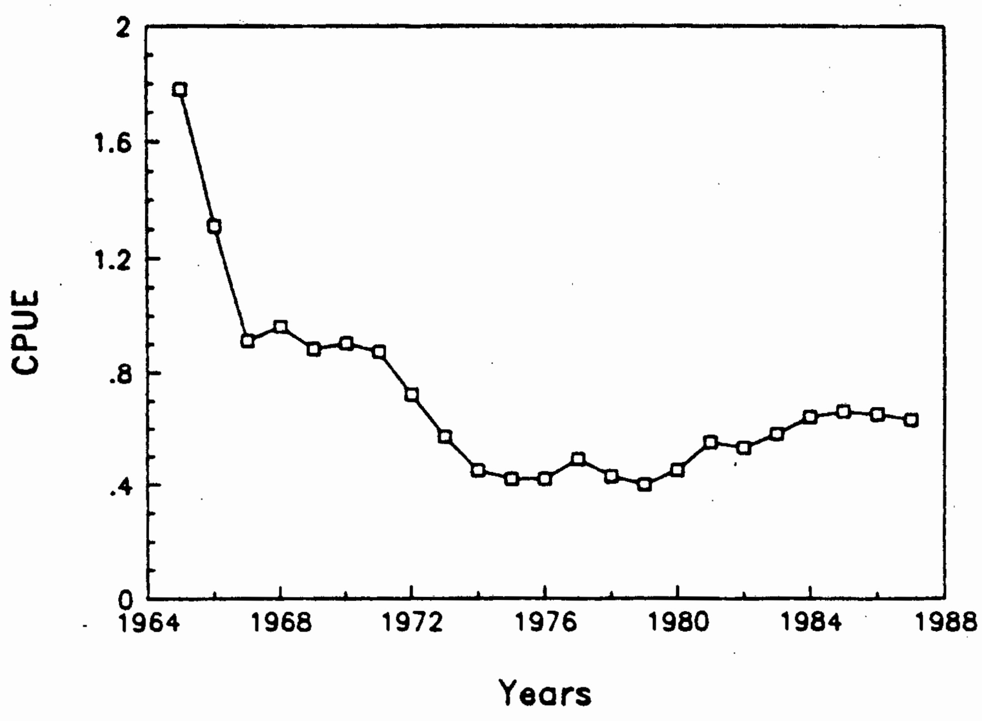


Figure 1.2: Cpue trend (in metric tons per OTB-7 hours fished) for ICSEAF Divisions 1.3 + 1.4.

The increasing fishing effort made a substantial impact on stock density, and cpue indices in all Divisions dropped markedly between the years 1965 and 1972; in Divisions 1.3 + 1.4, for example, the cpue declined by over 50%, indicating that (in a Schaefer model context) the stock was biologically overexploited (Fig. 1.2). The two major hake species were exploited to differing degrees in different areas, *M. paradoxus* dominating the catch off the Cape Peninsula, for example, while *M. capensis* was predominant on the Agulhas Bank (Payne 1988).

As a result of the rapid increase in fishing effort, the South African Division of Sea Fisheries initiated a research programme in 1966 which concentrated on the collection of catch-effort statistics for hake, and in 1972 ICSEAF was established to investigate and control exploitation of the fish resources in the South East Atlantic. This large area was divided into 8 Subareas (some of which are shown in Fig. 1.1), of which Subareas 1 and 2 correspond to those regions which provide the bulk of the Cape hake catch. For management purposes, each Subarea was further sub-divided into Divisions. The hake populations in four sets of these Divisions: Divisions 1.3 + 1.4, 1.5, 1.6 and 2.1 + 2.2 were assumed to be separate, and in consequence they have been managed independently. [Recent work by Payne *et al.* (1988) suggests, however, that the stocks in Divisions 1.5 and 1.6 may overlap.] After South Africa declared a 200 mile Exclusive Fishing Zone (EFZ) in 1977, quotas in Division 1.6 and Subarea 2 (South African EFZ) were set by the South African authorities based on recommendations made by ICSEAF. Although an EFZ has been declared by Namibia, this is not recognised internationally because of the territory's political uncertainty, and ICSEAF continues to regulate the hake fisheries off Namibia.

In an initial attempt by ICSEAF to reduce fishing effort, a minimum mesh size was enforced. For hake, this was initially 102mm, but after further research had indicated that it should be increased, a recommendation for a minimum mesh size of 110mm was instituted in July 1977. However, Davies *et al.* (1980) conclude from yield-per-recruit analyses, that this restriction probably had little or no effect in terms of altering the age composition of the catch.

From 1977 to 1983 recommended quotas were based on the use of Gulland's (1961) effort-averaging procedure in conjunction with Fox's (1970) formulation of the surplus production function (see Section 3.6 for a description of this). It is possible that the Fox form of the surplus production function was chosen over alternatives because it provided more accurate fits to the data available at the time (Andrew 1986). In order to allow the stocks to recover without restricting the industry excessively, a policy was implemented which aimed to maintain catches below the annual sustainable yields, in general by use of the $f_{0.1}$ strategy (see Chapter 4). However, after it was argued (ICSEAF 1983) both that the Gulland procedure was producing unsatisfactory fits to the data, and that allowance should be made in the estimation of quotas for changing catch rates from one year to the next, a policy of setting quotas based on the average results of three "dynamic" production models was subsequently employed (see Chapter 5). At its 1987 meeting, ICSEAF agreed that the averaging should in future involve weighting each quota estimate by a measure of its precision (ICSEAF 1987). The quotas set by ICSEAF for the period 1977 to 1988 are given in Table 1.2.

Table 1.1: Catches of Cape hake in metric tons by nation and year for all ICSEAF Divisions combined. Statistics are taken from the ICSEAF Statistical Bulletins. Entries in the final column represent the average percentage of the catch taken by each nation from 1981 to 1986.

Country	Years						% of Total Catch
	1981	1982	1983	1984	1985	1986	
Angola	-	-	-	5	16	-	0.00
Bulgaria	-	1322	4667	6004	302	393	0.45
Cuba	-	263	15318	23484	13202	5779	2.06
DDR	261	1147	2275	3593	2565	1401	0.40
Iraq	2	2	-	-	-	-	0.00
Israel	6149	4197	4610	4404	2529	-	0.78
Italy	-	-	-	-	694	-	0.02
Japan	4285	3732	991	935	2233	1583	0.49
Korea	-	97	444	103	-	-	0.02
Poland	4383	187	726	11073	24442	5509	1.65
Portugal	14178	12111	17581	25941	31654	30980	4.70
Rumania	274	6221	7300	8618	7307	8455	1.36
RSA	143905	156858	137619	152499	183228	182089	33.97
Spain	135051	139099	130353	122004	136377	147942	28.80
USSR	33943	114093	135013	137595	137283	153923	25.29
Others	-	-	277	-	-	-	0.00
Total	342431	439329	457174	496258	541832	538054	100.00

Table 1.2: Hake quotas recommended by ICSEAF for the period 1977 to 1988 and the catches actually taken. Statistics are obtained from the ICSEAF Annual Reports.

Year	ZONE I		ZONE II	
	Quota Set	Catch Taken	Quota Set	Catch Taken
1977	536 000	431 483	164 000	143 141
1978	480 300	379 390	147 700	141 381
1979	415 900	310 175	150 000	146 915
1980	320 000	171 848	112 000	149 370
1981	211 841	211 534	140 000	136 326
1982	352 000	307 078	127 700	134 012
1983	413 000	339 590	115 200	115 369
1984	413 000	370 640	129 000	126 493
1985	429 000	411 604	126 000	129 902
1986	481 000	407 200	133 000	129 906
1987	411 000	392 000	138 000	137 477
1988	411 000	-	138 000	-

Note: i) Entries marked "-" denote data which are currently unavailable

ii) Zone I = Divisions 1.3 + 1.4 and 1.5

Zone II = Divisions 1.6 and 2.1 + 2.2.

2 HAKE BIOLOGY

2.1 Genealogy

Three hake species [*Merluccius capensis* Castelnau (shallow water hake), *Merluccius paradoxus* Franca (deep water hake) and *Merluccius polli* Cadenat (Benguela hake)] are caught in the hake fishery in the southeast Atlantic. *M. polli* is only caught off northern Namibia and Angola, and for the rest of this study will be regarded as a part of the *M. paradoxus* stock which is found in deep water to the south of the area in which *M. polli* is dominant. The other two species are collectively called Cape hake. All these species are related to the cod-like fishes of the Order Anacanthini and have behaviour patterns similar to those of the European hake (*M. merluccius*). *M. paradoxus* was originally regarded as a sub-species of *M. capensis* (Franca 1962), but the two are now regarded as separate species.

Differences in gill structure, otolith morphology, pectoral fin length, number of vertebrae and gill rakers, relative eye size, colour of the anal fin and body shape for *M. capensis* and *M. paradoxus* have been noted by Konchina (1987), Van Eck (1969) and Botha (1980). The number of vertebrae has been shown by Van Eck (*op. cit.*) to be statistically different at the 5% level [49.9(s.e. 0.7) and 55.2(s.e. 0.69) for *M. capensis* and *M. paradoxus* respectively]. Differences in the gill tubercles have also been noted (Botha *op. cit.*), *M. paradoxus* having a black area in the centre of its tubercles which is not present in *M. capensis*. The tubercles of *M. paradoxus* also appear to be squarer in shape than those of *M. capensis*. The taxonomic status, distribution and biology of the genus *Merluccius* are reviewed by Botha (*op. cit.*) and Inada (1981).

2.2 Distribution

Cape hake are caught in shelf waters off the southern African coast from the Cunene River in the north (17^0S) to as far east as East London (28^0E) (see Fig 1.1). *M. capensis* lives closer inshore than *M. paradoxus*, but because there is a size gradation by depth, larger fish living deeper than small ones, large *M. capensis* cohabit with, and feed extensively on small *M. paradoxus* (Payne *et al.* 1987). Table 2.1 provides a rough classification of the ICSEAF Divisions (see Figure 1.1) according to the dominant hake species caught in each.

The major proportion of the hake stock is currently found at depths of between 200 and 400m (Payne *et al.* 1988), though large numbers of juvenile *M. capensis* live inshore of this. Botha (*op. cit.*) notes that *M. capensis* of length less than 40cm are generally found in water up to 220m deep, with the larger individuals at depths of up to 440m. A maximum depth of 600m for *M. capensis* is reported by Kawahara and Nagai (1980); however, *M. paradoxus* is found south of 22^0S at depths of between 150 and 920m along the continental shelf (Kawahara and Nagai *op. cit.*, Botha *op. cit.*). (*M. polli* is dominant in deep water north of this latitude.) Between the depths of 150-440m (Botha 1980) and 200-400m (Inada 1981) juveniles of *M. paradoxus* sp. coexist with the larger individuals of *M. capensis* (Botha *op. cit.*, Inada 1981); this phenomenon is uncommon among the adults of the two species (Badenhorst 1984), although it is possible that this may occur in some areas, owing to the narrowness of the continental shelf. Some migration between areas possibly occurs, in particular a southwestward migration of juveniles from the northernmost nursery areas in Division 1.6 and the southernmost ones in Division 1.5 (near the Orange River) has been suggested (Payne *et al.* 1987, 1988).

2.3 Spawning behaviour

The spawning behaviour of Cape hake shows marked spatial as well as interspecific variation. Hake generally mature relatively late [Konchina (1987) notes that individuals of *M. capensis* sp. first reach maturity at three years, at a length of over 30cm], but over a short space of time. 50% of the *M. capensis* stock is already mature at a length of 25cm in the case of males and 41cm in the case of females on the southeast coast (Botha 1980), and at lengths of 38cm or 47cm respectively on the west coast (Payne 1986). The length at 50% maturity of *M. paradoxus* on the southeast coast is much greater [42cm for males and 64cm for females (Botha *op. cit.*)], although on the west coast it is similar to that of *M. capensis*, i.e. 36cm for the males and 48cm for the females (Payne *op. cit.*).

Some spawning takes place virtually all year round (Botha 1980, Payne 1986) and it is not impossible that a female may spawn more than once a year. The spawning season on South Africa's west coast is bimodal, with a major peak in November/December and a less intensive period in February/March (Botha *op. cit.*) which is dominated by *M. paradoxus*. Although some co-existence of adults of the two species is possible owing to the narrowness of the continental shelf, Jones and Mackie

(1970) note that no interbreeding takes place, probably due to differences in the spawning areas of the species. Spawning areas are vertically separated from the fishing grounds and few spawning females are found in commercial catches (Botha 1980).

2.4 Feeding ecology

The prey species of Cape hake cover a wide spectrum, including crustaceans (e.g. amphipods, euphausiids and stomatopods) as well as fish (e.g. lanternfish, lightfish and juvenile hake) (Payne *et al.* 1987), and it appears that feeding may occur during the day as well as at night (Payne *et al. op. cit.*). Juveniles (less than 3 years old) eat predominantly euphausiids (Chlapowski 1977, Andronov 1987, Assorov and Kalinina 1979), which, off Namibia, may contribute up to 98% of their food intake. The percentage of fish in their diet increases until age four, after which it becomes the staple food item (Botha 1980, Chlapowski *op. cit.*, Assorov and Kalinina *op. cit.*, Payne *et al. op. cit.*), although crustaceans (mainly stomatopods and decapods) continue to contribute over 20% by mass of the total food consumption. Although Botha (*op. cit.*) proposes that hake do not compete for food with any other commercially exploited species, Andronov and Berenbeim (1983) suggest that competition between small *M. capensis* individuals (15-24cm) and adult horse mackerel ($\geq$ 21cm) is possible.

Cape hake become cannibalistic at a length of 40cm, after which juveniles are the most common item in their diet (Chlapowski *op. cit.*). In the case of the two species comprising the Cape hake stock, however, *M. capensis* tends to "cannibalise" juveniles of *M. paradoxus* sp., a phenomenon which is perhaps more accurately described as interspecific predation. The term cannibalism is used here, however, as the Cape hake stock is, in the main, regarded as a single species in most assessment exercises and for the purposes of this study. Chlapowski (*op. cit.*) reports that the stomach contents of 79.8% of adult (≥ 60cm) *M. capensis* individuals analysed contained juvenile hake. It may be concluded from this that a substantial proportion of the annual hake production is consumed by the stock itself (see also Bergh 1986).

Natural predators of Cape hake include sharks, snoek and other predatory fish, seals and dolphins (Bergh 1986). Botha (1980), however, postulates that these are unlikely to be a major threat to the stock, despite heavy exploitation by man. Estimates (in yr^{-1}) of the instantaneous rate of natural mortality, M [which, as a result of cannibalism, can be expected to be related to adult abundance (Chlapowski 1977, Botha *op. cit.*), but which for simplicity is usually assumed to be constant], range from low estimates of 0.25 (Newman *et al.* 1976, Draganik 1976, Lleonart *et al.* 1985b) and 0.3 (Prenski 1980, Davies *et al.* 1980, Leslie 1985) to high estimates larger than 0.4 (Andrew 1986). Andrew (*op. cit.*), using Pauly's (1980) formula and some of the estimates of the length and growth parameters (see Section 2.5. below) presented in the literature, reports that estimates of M may be far larger than previously suspected. Botha (*op. cit.*) and Payne (1986) report different estimates of M for each species (Table 2.2). Gasjukov and Dorovskikh (1988) estimate the component of natural mortality which is not dependent on adult biomass to be 0.6. This estimate has been found to be very imprecise (Butterworth 1988b), however, having a 95% confidence interval of [0.2,>0.75].

2.5 Biological parameters

Individuals of *M. capensis* sp. may reach an age of 11 years or more, and a length of over 1m (~4kg). The lifespan of *M. paradoxus*, however, depends on the sex of the individual, males rarely exceeding 50cm (5 years), while the females may attain a length of 80cm (9 years) (Botha 1980). Several authors have commented that females of *M. paradoxus* sp. tend to live longer than the males (Chlapowski *op. cit.*, Kono 1980, Payne 1986) and postulate that this could be due (partially at least) to the diversion of energy into reproduction rather than growth at an earlier age in males (males mature earlier than females). The females of both species grow faster than the corresponding males. Length as a function of age has been modelled by the Von Bertalanffy equation :

$$\ell_t = \ell_\infty(1 - e^{-\kappa(t-t_0)}) \qquad (2.1)$$

where ℓ_t - length at age t,

ℓ_∞ - asymptotic (or maximum) length,

κ - growth rate parameter and

t_0 - 'age' at zero length,

while mass as a function of length is well represented by the curve :

$$w_t = a(\ell_t)^b \qquad (2.2)$$

where w_t - mass at age t and

ℓ_t - length at age t.

Typical length and growth parameters for Cape hake reported in the scientific literature are given in Table 2.3.

Table 2.1: Divisions of the ICSEAF Convention area as categorised by the dominant hake species caught in each. The limit given in Column 3 is the approximate depth at which dominance changes (Kawahara and Nagai 1980).

Division	Dominant shallow water species	Limit (m)	Dominant deep water species
1.3	*M. capensis*	400	*M. polli*
1.4	*M. capensis*	450	*M. paradoxus*
1.5	*M. capensis*	350	*M. paradoxus*
1.6	*M. capensis*	300 - 350	*M. paradoxus*
Subarea 2	*M. capensis*	300 - 350	*M. paradoxus*

Table 2.2: Estimates of the instantaneous rate of natural mortality (M) in yr^{-1} for Cape hake off South Africa (Divisions 1.6, 2.1 + 2.2) by species and sex (Botha 1980, Payne 1986).

<table>
<tr><th rowspan="2">Species</th><th rowspan="2">Sex</th><th colspan="2">Rate of Natural Mortality</th></tr>
<tr><th>West Coast</th><th>S.E. Coast</th></tr>
<tr><td>M. capensis</td><td>Male</td><td>0.40</td><td rowspan="2">0.46</td></tr>
<tr><td>M. capensis</td><td>Female</td><td>0.33</td></tr>
<tr><td>M. paradoxus</td><td>Male</td><td>0.44</td><td rowspan="2">0.70</td></tr>
<tr><td>M. paradoxus</td><td>Female</td><td>0.34</td></tr>
</table>

Table 2.3: (a) Typical estimates for the parameters of the Von Bertalanffy length-age relationship for Cape hake (equation 2.1), (b) estimates of the parameters of the length-age relationship derived by Payne (1986) using data collected in Divisions 2.1 + 2.2 and (c) typical estimates for the parameters of the mass-length regression for Cape hake (equation 2.2). (Where available, specific details of the sample used to obtain the estimates are given.)

Author	Details	ℓ_∞ cm	κ yr^{-1}	t_0 yr
Botha (1980)	Ages 4 to 11 only	115.7	0.130	-0.444
Botha (1980)	*M. capensis* (males)	105.8	0.146	-0.928
Botha (1980)	*M. capensis* (females)	173.1	0.066	-0.012
Botha (1980)	*M. paradoxus* (males)	61.7	0.311	-0.725
Botha (1980)	*M. paradoxus* (females)	112.8	0.121	-0.172
Davies *et al.* (1980)	Division 1.6	118.6	0.119	-0.179
Isarev (1983)	Divisions 1.3 + 1.4	134.5	0.085	-0.815
Kolender (1975)	Divisions 1.3 + 1.4	174.8	0.064	-0.365
Leslie (1985)	Division 1.6	125.4	0.113	-0.040
Leslie (1985)	Divisions 2.1 + 2.2	167.3	0.080	-0.378
Obregon (1980)	Divisions 1.3 + 1.4	170.9	0.056	-0.958
Pozo (1976)	*M. capensis*	111.1	0.120	-0.240
Prenski (1978)	Divisions 1.4 + 1.5	125.2	0.211	-0.106

(b)

Species	Sex	ℓ_∞ cm	κ yr^{-1}	t_0 yr
M. capensis	Male	92.8	0.266	0.733
M. capensis	Female	125.5	0.160	0.421
M. capensis	Both	130.7	0.144	0.296
M. paradoxus	Male	52.6	1.056	1.376
M. paradoxus	Female	109.0	0.159	-0.413
M. paradoxus	Both	102.9	0.198	0.245

(c)

Author	Details	a kg	b
Chalmers (1976)	Division 1.6	0.0062	3.031
Draganik (1976)	Division 1.6	0.0095	2.885
Isarev (1983)	Divisions 1.3 + 1.4	0.0170	2.820
Kolender (1975)	Divisions 1.3 + 1.4	0.0068	2.990
Pozo (1976)	*M. capensis*	0.0011	2.840
Prenski (1978)	Divisions 1.4 + 1.5	0.0070	2.991
Prenski (1980)		0.0070	2.995
Terre (1983)		0.0100	2.900

3 THEORETICAL OVERVIEW OF SURPLUS PRODUCTION MODELS

3.1 Introduction

Models (simplified and usually mathematical representations of natural processes) are used in fisheries research to make predictions about the future state of a resource and to explain and understand its history. Mathematical models, which are the only models considered here, allow the modeller's ideas to be expressed in the concise language of mathematics, thus forcing a degree of consistent thinking. Furthermore, models can be used to provide a quantitative method of comparing and contrasting different harvesting strategies by investigating the effects of these on the (model-predicted) state of the resource. The accuracy with which a model can make such predictions depends critically on the assumptions and simplifications upon which it is based.

Simple models, such as those discussed in this study, may provide "better" predictions than those obtained from more complex models. This could happen, for example, if the more complex model required the estimation of additional parameters from the available data used to fit the model, resulting in a large increase in the "error due to estimation" (Linhart and Zucchini 1986 - see Chapter 7 for more details).

It is possible for the same simple model to arise from more than one set of assumptions. The results from such a model may, therefore, be independent (to a degree) of its underlying assumptions, and, as these assumptions are usually very difficult to test in practice, this allows the model to be more robust to the actual "underlying" structure of the resource.

This study examines the class of fisheries models called surplus production (or stock production) models. These are often used in fisheries management instead of methods which utilise catch-at-age information (such as VPA), because the catch-at-age data are often unreliable (or unavailable). Surplus production models have minimal data requirements (usually only annually-aggregated catch and effort information is used).

3.2 Data available for use in surplus production modelling

The data provided by a fishing industry are often limited to the time series of annual catches, $\{C_i\}$, and annual catch-per-unit effort (cpue), $\{(C/E)_i\}$. The cpue series is often shorter than the corresponding catch series, as collection of effort statistics usually starts only after the fishery has developed sufficiently to warrant the research needed for scientifically based management. This is the case with the data set for the hake fishery in Division 1.6, which includes catch data from 1917, while the cpue data are only available from 1955.

The catch-effort data collected by ICSEAF do not distinguish between the two hake species, *M. capensis* and *M. paradoxus*, except for the last 5 years in Divisions 1.6 and 2.1 + 2.2, and thus the accumulated biomass of these two species defines the total biomass of the hake stock in any Division, except in Division 1.3, where the stocks making up the total biomass are *M. capensis* and *M. polli* (which, again, are not distinguished in the catch data). The reported catch for year i,

C_i, is the total mass (in tons) of fish caught during the year. The nominal (or live) mass rather than landed mass (which corresponds to headed and gutted fish) is used. [Catches up to 1972 for Divisions 1.6 and Subarea 2 have been incremented by 39% to take into account bias caused by the discarding of young fish during this period (ICSEAF 1978).] The reported catch always tends to underestimate the total mortality due to fishing, as the mass of fish which die as a result of passing into the net and subsequently slipping out of it, are not recorded. It is assumed, however, that this represents a sufficiently small fraction of the total fishing mortality that any bias resulting from it can be ignored.

The fishing effort for year i, E_i, in any Division is defined as the sum of the standard effort of all vessels fishing in that Division during year i. The standard effort of a particular vessel is defined as the product of its fishing power and the time it spends fishing (actual effort). Except for Division 1.6, the unit of actual effort is trawler hours (the amount of time in hours that the trawl nets are towed along the bottom). In Division 1.6 this unit is trawler days (the number of days on which a vessel fishes during the year). In order for trawler days to provide an unbiased relative estimate of the total number of hours trawled, the steaming time to the fishing grounds should be minimal (in Division 1.6 the nets are usually dropped after only few hours steaming from the harbour) and the assumption is made that, over the history of the fishery, the same fraction of the day has been spent towing the trawl nets.

The fishing power of a vessel is defined by Gulland (1969) as the catch per unit fishing time taken from a given density of fish, and thus depends on tonnage, horsepower and fishing gear of the vessel. All the effort in a particular Division is standardised to that of a single type of vessel. Effort in Divisions 1.3 + 1.4 is standardised to Spanish OTB-7 effort (i.e. "otter trawl bottom", 7 tonnage class), that in Division 1.5 is calculated from pooled Spanish OTB-7 and South African OTB-5 data, while South African (ZAF) OTB-5 data are used in Divisions 1.6 - 2.2.

The total effort calculated will be biased if power factors are incorrectly calculated or not updated sufficiently frequently. [Whether the existing estimates of power factors are adequate is currently an area of concern - see Butterworth (1988a).] A further potential source of bias lies in the total effort figures, which are computed from the directed effort and catch data from a few fleets only (i.e. those which have produced large catches in a given Division over a long period of time and at high levels of effort, and from which estimates of cpue can be obtained with relatively high precision). This procedure assumes that cpue for the part of the fishery considered is representative of the fishery as a whole. This is questionable, however, as in several cases the trends in the cpue series available can be shown to be statistically significantly different from each other [i.e. at least one of them is not measuring the underlying biomass signal (Butterworth *et al.* 1986b)], although obtained from fleets fishing in the same Division. The catch-effort data for Divisions 1.3 and 1.4 are combined, as the two Divisions show similar cpue trends. In addition, the data for Subarea 2 are pooled, as catches in Divisions 2.2 are very small (Andrew 1986).

Estimates of biological parameters such as growth and natural mortality rates are usually available from species studies [such as those of Inada (1981) and Botha (1980) (see Chapter 2)]. These parameters are used in some of the production models considered here (e.g. Schnute/Deriso and Shepherd). In recent years, in addition to the collection of simple catch and effort data, collection of otoliths for ageing purposes has been made, so that the age structure of the catch can be estimated. Although many estimation procedures (such as VPA) use these data, such procedures are not considered here. Regular direct surveys of the stock allow estimates of stock size which are independent of catch-effort data to be made, although they are relatively imprecise. Incorporation of direct survey estimates into production model estimation procedures is currently being undertaken (Andrew and Butterworth 1989), although these procedures are also not considered here.

Tables 3.1(a) to (d) summarise the catch-effort history of the ICSEAF Convention Area [excluding the pre-1955 catches for Divisions 1.6 which are listed in Andrew (1986)], although it is possible that some of the values given may since have been updated in the light of revised information.

3.3 General theory of surplus production models

Surplus production models are necessarily simplifications of reality. The stock under consideration is assumed to be closed (or a unit stock), as the rates of immigration and emigration are considered to be negligible compared with the rates of growth and natural mortality. The stock size (exploitable biomass is usually modelled, rather than total or spawning biomass) will increase as a result both of recruitment into the population of young fish which have become large enough to be selected by the fishing gear and have migrated into the fishing grounds, as well as of tissue growth in individual fish. Natural and fishing mortality are effects which reduce the population size. The magnitude of these two effects depends on factors such as the age- and size-structure of the population, environmental variation, spatial density patterns across the fishing grounds, and current and historical biomasses. Although it is likely that the population size will be influenced by interaction with other species (food availability, predation, etc.), the general surplus production model developed below assumes that this effect, along with spatial and environmental variation, is either insubstantial or essentially random. In the following, functions which represent rates of change are denoted by the use of upper case.

The rate of change of biomass at time t can be described by the equation :

$$\frac{dy(t)}{dt} = G(\tilde{y}(t))\, e^{u_t} - H(y(t),E_t) + v_t \tag{3.1}$$

where $y(t)$ is the exploitable biomass at time t,

$\tilde{y}(t)$ is the vector of past biomasses (i.e. at times t-1, t-2, t-3, ...),

E_t is the effort in year t - as effort data are usually reported on an annual basis, E_t also represents the average rate of effort directed at the stock during year t [for all the models described below, it is assumed that E(t) is constant during year t, but may vary between years],

G(.) is the instantaneous rate of surplus production, comprising the combined effects of all natural (i.e. excluding the fishery) processes which increase or decrease the population,

H(.) is the instantaneous rate of losses due to fishing caused by E_t units of effort - this is equivalent to the instantaneous rate of yield (catch) in year t and

u_t, v_t are components of noise (possibly related to environmental and species interaction effects) which are not explicitly modelled in equation (3.1); these are sometimes termed "process error".

The rate of change in biomass is thus assumed to be made up of only three effects: (i) $G(\tilde{y}(t))e^{u_t}$, the surplus production [which may depend not only on the current biomass, but also on the biomass at some time in the past (which allows for the time required for the juveniles to grow large enough to be selected by the fishery)], (ii) $H(y(t),E_t)$, the harvesting rate, which depends on the current biomass and on the amount of effort expended by the fishery at time t, and (iii) v_t, which represents a random (or unmodelled) effect (process error contribution) at time t.

This general model encompasses the "approximating family of models" [in the sense of Linhart and Zucchini (1986)] which are investigated in this study. By suitable choice of functional forms for G and H above, equation (3.1) can be made to behave like many of the familiar simple (non-age-structured) fisheries models in current use.

The surplus production function G() may be broken down into the major components affecting surplus production :

$$\tilde{G}(y(t)) = \tilde{R}(y(t)) + \tilde{T}(y(t)) - \tilde{M}(y(t)) \qquad (3.2)$$

where R(), T() and M() are the rates of reproduction (recruitment), tissue growth and natural mortality respectively. As M() is permitted to be a function of past biomasses, it is possible to specify sub-models in which natural mortality is not constant.

Simplifications can be made with respect to the losses due to fishing. The linear model:

$$h(y(t),E_t) = \frac{dC(t)}{dt} = q.E_t y(t) \qquad (3.3)$$

arises from the assumption that the population and fishing effort are randomly distributed over the fishing grounds and that a single additional unit of effort or of biomass produces a proportional increase in the catch. On the other hand, the pulse-fishing assumption of a very short fishing season in which the total catch is taken and during which natural mortality is assumed to be zero, leads to the non-linear model :

$$h(y(t),E_t) = \frac{dC(t)}{dt} = (1 - e^{-qE_t})y(t) \tag{3.4}$$

The parameter q in these two equations is called the catchability coefficient, and measures the manner in which the fishing gear is employed relative to the availability and vulnerability of the population. (For small E_t it can be interpreted as the proportion of y_t taken by one unit of effort.)

If the linear model is assumed (or E_t is small) then :

$$\frac{dC(t)}{dt} = q.E_t y(t) \tag{3.5}$$

Integrating equation (3.5) over year t gives :

$$C_t = q.\bar{y}(t).E_t \tag{3.6}$$

where C_t is the (gross) catch in year t,

E_t is the average standardised effort in year t and

$\bar{y}(t)$ is the average biomass in year t.

Dividing equation (3.6) by E_t then gives:

$$C_t/E_t = (C/E)_t = q.\bar{y}(t) \tag{3.7}$$

Thus, although $\bar{y}_t$ is seldom (if ever) known, relation (3.7) indicates that $(C/E)_t$ may be used as an index of abundance. In reality, equation (3.7) (or the "observation model") has random noise superimposed on it which is termed "observation error". The stochastic equivalents of equation (3.7) and its non-linear version (from equation 3.4) are assumed to be :

$$(C/E)_t = q\bar{y}(t)E_t e^{u_t} + v_t \tag{3.8}$$

and

$$(C/E)_t = (1 - e^{-qE_t})\bar{y}(t)e^{u_t'} + v_t' \tag{3.9}$$

(Note that, although errors in the measurement of catch and effort have not been considered in the above analysis, these may occur and could plausibly be incorporated into an extension of the system of equations derived above.)

Some of the estimation procedures described in Chapter 5 require that the harvesting rate H depends not only on the current biomass y(t), but also on past biomasses; the function $H[y(t),E_t]$ is thus generalised to $H[\tilde{y}(t),E_t]$.

Equation (3.1) and its generalisations discussed above can be transformed into a difference equation (discrete model) by splitting the derivative:

$$y_{i+1} = y_i + g(\tilde{y}_i).e^{u_i} - h(\tilde{y}_i,E_i) + v_i \tag{3.10}$$

where y_i is the population size at the beginning of year i,

$\tilde{y}_i$ is a vector of past biomasses (i.e. at times i-1, i-2, i-3, ...),

$g(\tilde{y}_i)$ is the increase/decrease in biomass resulting from natural processes,

$h(\tilde{y}_i,E_i)$ is the mass of fish removed from the population in year i by fishing, and

u_i, v_i are components of noise.

If a sub-model of either the general continuous [equation (3.1)] or general discrete [equation (3.10)] surplus production models has been mis-specified, it is likely that one or more of the noise terms will appear to be dependent on current and past biomasses; in this case, "error due to approximation" (Linhart and Zucchini 1986) can be expected. The other type of error which is likely to affect prediction is the "error due to estimation" (Linhart and Zucchini *op. cit.*), which is the error resulting from the attempt to estimate the model parameters from a data set of finite size. (More detail about these types of error is given in Chapter 7.) Even if a selected sub-model (with its error structure) is a very accurate representation of the underlying fishery (low "error due to approximation"), predictions may still be poor if the available data preclude precise estimation of the model parameters (high "error due to estimation"). This is the reason why, in some cases, simple models are able to make predictions with smaller overall error (i.e. the sum of the errors due to approximation and estimation) than are more complex models.

3.4 Fitting surplus production models to data

In order to fit the general surplus production model (as defined above) to real data, specific forms for g() and h(.) [or G() and H(.)] must be chosen and the dominant component(s) of noise selected. To enable sensible estimates of parameters to be made from a fit of the historical data (C_i, i=1, 2, .. ,n; E_i, i=1, 2, .. n) to a sub-model of the general continuous model [equation (3.1)] or of its discrete formulation [equation (3.10)], the statistical criteria of repeatability and stationarity must be assumed.

Walters (1986) defines a strictly repeatable process as a "process from which the same mean response is obtained before and after any disturbance of the stock, irrespective of the size of the disturbance". For example, recruitment may be assumed to dependent on (current) stock size alone and not on the age-structure, so that the expected recruitment at a given stock size always remains constant. No stock condition can be strictly repeatable because large disturbances lead to irreversible loss of genetic and spatial structures (Walters *op. cit.*). However, in a "well-managed" stock, large disturbances are unlikely to occur, and so processes need only be **weakly** repeatable (i.e. the same mean response will be obtained after any disturbance that is likely to occur in practice). If a process is non-repeatable, the hypothesised functional relationships may contain serious "error due to approximation", i.e. certain basic sub-processes are missing from the model, and biased estimates may be obtained if historical data are used to parametrise it (Walters *op. cit.*).

A stationary process is one for which the probability distribution of a response from the process is stable over time. This is a stronger condition than repeatability, which only requires that the mean value remains stable. As tests for repeatability and stationarity are often very difficult (if not impractical) to perform, all the stocks considered in this study are assumed to manifest at least weak repeatability.

In order to illustrate the estimation of the parameters of the general surplus production model, the discrete formulation given by equation (3.10) is used. After noting that $h(\tilde{y}_i, E_i)$ is the discrete form of the yield function (and can therefore be replaced by C_i), equation (3.10) with its (linear) stochastic observation model [equation (3.8)] may be represented as follows :

$$y_{i+1} = y_i + g(\tilde{y}_i).e^{v_i} - C_i + s_i \tag{3.11}$$

$$C_i = q.y_i.E_i.e^{z_i} + u_i \tag{3.12}$$

where y_i is the total exploitable biomass at the beginning of year i,

$\tilde{y}_i$ is the vector of (discrete) historical biomasses up to and including year i,

$g(\tilde{y}_i)$ is the discrete form of the surplus production function,

E_i is the effort in year i and

s_i, u_i, v_i, z_i are components of random noise - s_i and v_i contribute to "process error", and u_i and z_i to observation error".

The parameters of this model are generally estimated by minimising some function of the observed and predicted cpue :

$$SS = \sum_{i=1}^{n} w_i \, [f(C/E_i) - f(\widehat{C/E_i})]^2 \tag{3.13}$$

where $(C/E)_i$ is the observed cpue in year i,

$(\widehat{C/E})_i$ is the model-predicted cpue for year i,

n is the number of data points used,

w_i is the weight assigned to the data point in year i (weights are constrained so that $\Sigma w_i = n$) and

f is a transformation.

The non-linear minimisation routine E04FCE [NAG(1977)] has been used to estimate the values of the parameters which minimise SS for the results reported in this thesis.

The choice of error model (which relates to the appropriate transformation function f and weighting function w) can be important in obtaining estimates of management variables which have as small a variance as possible (Butterworth and Andrew 1987). This is called the "minimisation criterion" and should be chosen to ensure that the residuals are homoscedastic [i.e. the variance is independent of the expected cpue (as transformed under f) when $w_i = 1$, or otherwise is proportional to w_i^{-1}] when the model is fitted to real data. The type of error model chosen depends on where the dominant noise term is assumed to occur in the equations. The two extreme types of error model are "process error" and "observation error". For the purposes of this study, it is assumed that estimates of catches are reasonably accurate and that the cpue reflects all the variability in the data.

- The process error model

This type of error model assumes that all noise is caused by natural processes (e.g. temperature anomalies, increase in the abundance of predators, etc.). The error terms (v_i, s_i) in equation (3.11) are assumed to dominate those in equation (3.12), which expresses the relation between cpue and biomass. [The observation model is thus assumed be exact (i.e. it contains no noise)]. Here, the choice of the transformation function f will depend on *a priori* ideas of the process error variance as a function of biomass, because paucity of data usually precludes the use of statistical methods which have the power to distinguish between alternative transformations under tests for heteroscedasticity.

- The observation error model

The dominant noise is assumed to be in equation (3.12) (i.e. in the observation model), which provides an index of the population size, and the population dynamics [equation (3.11)] are assumed to be deterministic. For this type of error model, an estimate of the initial biomass level is needed in the model fitting process in order to start the biomass series. If such a model is selected, but the dominant noise is in equation (3.11), serial correlation can be expected in the residuals and this may bias the parameter and variance estimates obtained using least squares estimation. Two of the possible minimisation criteria (transformation functions f) which have been proposed for the observation error model are described below; the choice between them depends on which of the noise terms in equation (3.10) is dominant. These noise contributions may arise from :

(i) Sampling error (u_i). This implies that the precision with which cpue can be estimated depends on the size of the catch taken. Kirkwood (1981) suggests that fishing may be approximated by a Poisson-like process (i.e. with variance proportional to the mean) and advocates the use of $\sqrt{C}$ minimisation, as this provides asymptotic homoscedasticity of the residuals. The minimisation criterion is then:

$$SS = \Sigma\ (\sqrt{C_i} - \sqrt{\hat{C}_i})^2 \tag{3.14}$$

$$= \Sigma\ E_i\ \{\sqrt{(C/E)_i} - \sqrt{(\widehat{C/E})_i}\}^2$$

Cpue data for whale populations have been analysed by de la Mare (1986), who found that the c.v.'s of the residuals after linearly detrending the data do not decrease as the size of the catch increases, in spite of using this criterion. In such situations the square-root transformation does not provide homoscedastic residuals, as large catches receive too large a weighting, and estimates obtained by least squares tend to be less precise as a result. De la Mare (*op. cit.*) concludes that large catches do not improve cpue estimates (although they do provide greater contrast in the data set).

(ii) Catchability fluctuations (z_i). Changing environmental factors, seasonal migration and behavioral/distibutional changes tend to produce inter-annual catchability fluctuations. As it is expected that there are a large number of these effects, each of which is likely to be independent and to have a multiplicative effect, the central limit theorem implies that the sum of the logarithms of the magnitudes of these effects approaches a normal distribution, and thus that $\ell n(C/E)$ minimisation is the most appropriate transformation to use :

$$SS = \Sigma\ [\ell n(C/E)_i - \ell n(\widehat{C/E})_i]^2 \tag{3.15}$$

> Gulland (1956) notes that this transformation has had the effect of stabilising the variance of catch-effort data for the North Sea demersal trawl fishery. In addition, empirical distributions of cpue are often highly positively skewed (Gulland *op. cit.*, Moyle and Lound 1960, Bannerot and Austin 1983), as would be expected if cpue is log-normally distributed.

In the light of de la Mare's (*op. cit.*) results in particular, equation (3.15) will be used in preference to equation (3.14) for the analysis that follows.

Although (in the ICSEAF literature) one of the above minimisation criteria (transformation functions f) has always been selected, together with an explicit choice of either process or observation error dominance, there is no *a priori* reason why there should not be comparably substantial noise both in the stock dynamics and in the population index. There are, however, serious statistical difficulties associated with attempting to incorporate noise occurring simultaneously in both the catching process and in the stock dynamics, into a simple minimisation criterion (Reed 1986).

Ludwig *et al.* (1988) describe an approximate method of incorporating both observation and process error into an estimation procedure. Following the nomenclature of these authors, this will be called total least squares (TLS) method and involves minimising the weighted sum of the squares of the estimated observation errors $\{\hat{v}_i\}$ and the estimated process errors $\{\hat{w}_j\}$:

$$SS = \frac{1}{1 - \lambda} \sum_i \hat{w}_i^2 + \frac{1}{\lambda} \sum_j \hat{v}_j^2 \tag{3.16}$$

Ludwig *et al.* (*op. cit.*) report that SS depends only weakly on the choice of λ [the ratio of σ_w^2 to $(\sigma_w^2 + \sigma_v^2)$] and, following their example, λ is taken to be 0.5 here. (Note that λ has to be pre-specified; it cannot be estimated satisfactorily from the data.)

In order to estimate the process and observation errors $\{w_j\}$ and $\{v_j\}$, it is assumed that :

1) Effort is lognormally distributed :

$$E_i = e_i e^{v_i}$$

where E_i is the observed annual effort in year i,

e_i is the true annual effort in year i and

v_i is an error term drawn from the distribution $N(0,\sigma_v^2)$.

2) There exists a function which relates catch, cpue and biomass; any of the observation models (3.4) to (3.6) can be used.

3) There is a dynamic equation relating the biomass in various years, which is of the form :

$$y_{i+1} = \tilde{g}(y_i)e^{w_i} - C_i \tag{3.17}$$

where y_{i+1} is the biomass in year i+1,

$\tilde{g}(y_i)$ is the sum of the original biomass and surplus production in year i,

C_i is the catch in year i and

w_i is the process error term in year i.

The $\{\hat{v}_i\}$ are estimated as parameters along with the other model parameters. Given the series of estimated observation errors $\{\hat{v}_i\}$ and the model parameters, estimates of the process errors can be made as follows :

a) the estimated effort in year i, $\hat{e}_i$, is estimated by $E_i e^{-\hat{v}_i}$

b) the biomass in year i is estimated from the relation between catch, effort and biomass by replacing effort by its estimated value, $\hat{e}_i$

c) w_i can then be calculated from equation (3.17).

In many cases, it is only possible to estimate (n-1) process errors because both y_{i+1} and y_i are required in equation (3.17).

3.5 Equilibrium

A population is considered to be in equilibrium (in the context of surplus production models) if its biomass remains constant over time [i.e. $y_{i+1} = y_i$ or $dy(t)/dt = 0$]. Making this assumption throughout the history of the fishery when estimating model parameters is called the "continuous equilibrium assumption" and implies that the catches taken are exact measures of the surplus production of the stock. This assumption substantially simplifies the process of parameter estimation; however, it has been criticised in the scientific literature (see Chapter 8). "Dynamic" models are those which do not make the continuous equilibrium assumption (Butterworth 1988c) and are the major focus of this study, as it is extremely unlikely that the observed cpue data do reflect equilibrium states.

3.6 Traditional surplus production functional forms

Traditionally, the surplus production function $g(\tilde{y})$ has been chosen to be very simple, usually depending on current biomass alone, i.e. $g(\tilde{y}) = g(y(t)) = g(y)$. In this section, nine possible surplus production functions with their underlying assumptions are considered.

The choice above means that the rate of natural increase $g(y)$ is assumed to react immediately to changes in biomass (i.e. no time delays). This, however, implies that current recruitment reacts immediately to changes in current biomass, which cannot occur in practice, as recruits are born some years before they are recruited into the exploitable stock [see Walter (1973) for surplus production functions which incorporate time delays]. It is implicitly assumed that the age-structure of the population has a negligible effect on the production rate (i.e. the size of the biomass rather than its age-structure determines the rate of production). For this to be true, the age composition of the stock (i.e. the fraction of the total biomass falling into each age-class) must remain virtually constant throughout the history of the fishery, as fecundity, growth and mortality are age-specific. This assumption is fairly well met if the intensity of fishing effort remains almost constant, as the age-composition tends to stabilise under a strategy of constant fishing mortality.

Any proposed deterministic surplus production function should be consistent with certain basic biological constraints:

(i) $g(0) = 0$ (i.e. no adults, no production)

(ii) $g(K) = 0$ [a population of size K (average pristine level) is stable and will remain at this level (in a deterministic context)], i.e. there are natural limits to the growth of the unexploited resource

(iii) $g(y) > 0$ for at least some values of y in the range $[0,K]$.

These assumptions imply that, in the absence of fishing, a stock once disturbed will tend to return to K, which is called the environmental carrying capacity. The functions chosen for $g(y)$ have maxima at biomasses which are well below this level, however. As no state variables other than biomass are used in the surplus production function, it is assumed that the population is regulated by density dependent effects (e.g. cannibalism, food availability, etc.) which are implicitly incorporated in $g(y)$ itself.

The surplus production function may incorporate depensatory effects over some part of the $[0,K]$ domain. In a stock exhibiting "critical depensation" (Fig. 3.1), if the biomass drops below some critical population y_c, it cannot recover and becomes extinct within a finite time. Figure 3.2 illustrates a "predator pit" situation. If the population drops below y_a, its interaction with its natural predators will cause it to decline still further to y_b; at this point the biomass becomes too small to satisfy the predators and they switch to other prey species. If the population is then able to recover to a level greater than y_b, the predators may switch again and drive it back to y_b. The population is thus maintained by its predators at the new stable equilibrium level, y_b. The surplus production models discussed

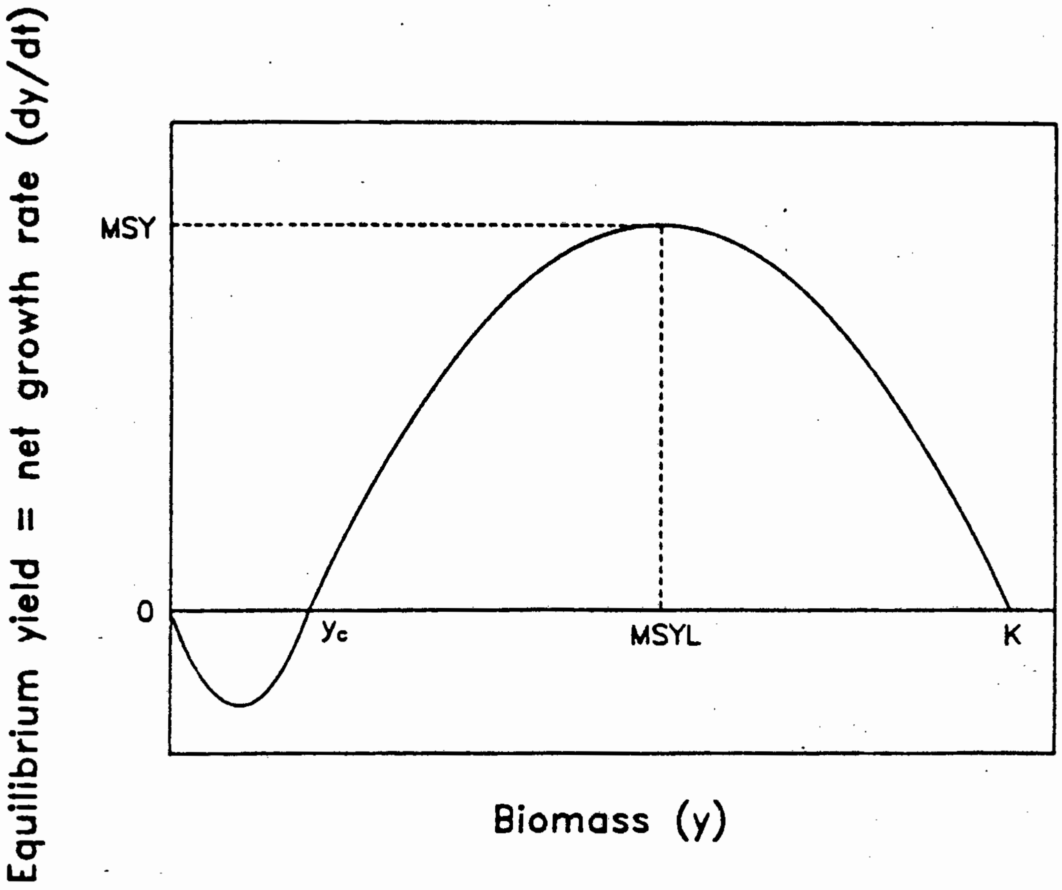


Figure 3.1: A surplus production curve showing critical depensation as a function of biomass. Once the biomass decreases below y_c, the population can never recover and goes to extinction.

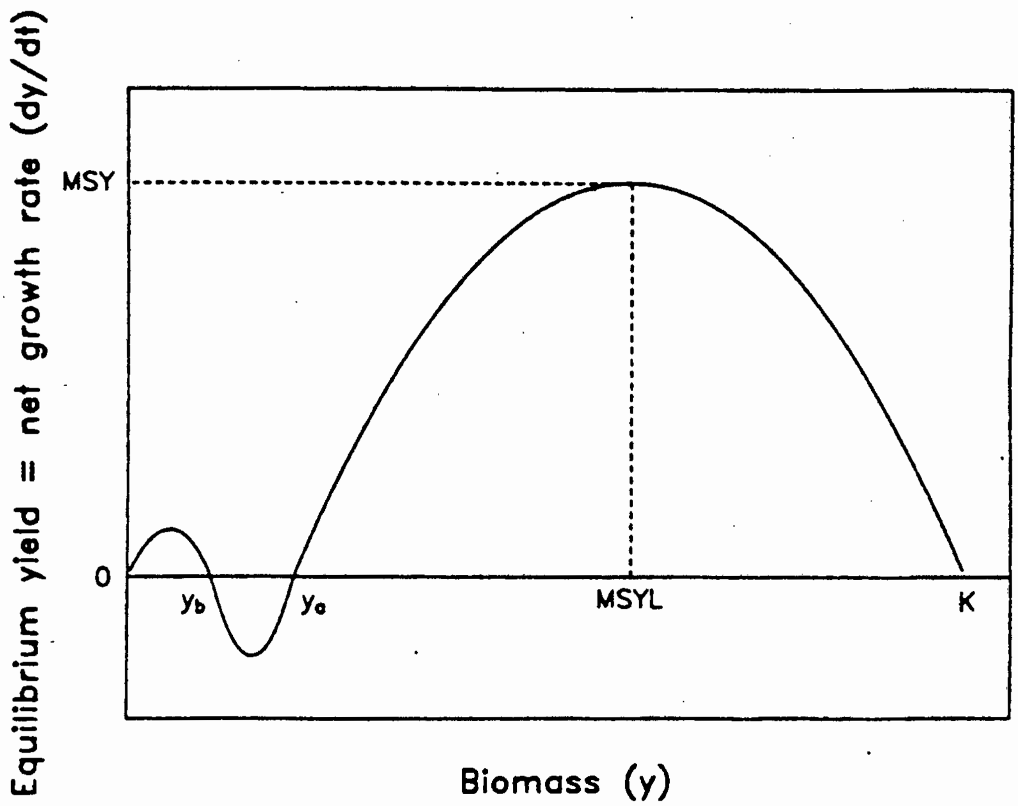


Figure 3.2: A depensatory surplus production curve for a prey population with "a predator pit", as a function of biomass. Once the stock is reduced below y_a the predators prevent it increasing beyond the lower of the two unexploited stable equilibrium levels, y_b.

below do not incorporate these effects, as it is assumed that the population never drops to the low levels at which they (may) begin to take effect.

Nine of the many different formulations of the surplus production function g(y) are :

i) Schaefer (1954,1957): $g(y) = ry(1 - y/K)$

ii) Fox (1970): $g(y) = ry[1 - \ell n(y)/\ell n(K)]$

iii) Pella-Tomlinson (1969): $g(y) = ry[1 - (y/K)^p]$

iv) Walters (1986): $g(y) = ry^{\alpha}(1 - y/K)^{\beta}$

v) Shepherd (1982): $g(y) = ay/[1 + (y/b)^c]-My$

vi) Shepherd (1987) (special case of v): $g(y) = ay/(1 + y/b) - My$

vii) Schaefer-SQ Butterworth *et al.* (1986): $g(y) = rK/2\mu\{1-|1-2y/K|^{\mu}\}$

viii) Ricker (1954): $g(y) = \alpha_1 ye^{-\beta_1 y} - y$

ix) Beverton-Holt (1957): $g(y) = \alpha_1 y/(1 + \beta_1 y) - y$

x) Power [Ludwig *et al.* 1988]: $g(y) = \alpha_1 y^{\beta_1} - y$

where y is the current biomass,

r is the intrinsic growth rate parameter (although in some cases $(dy/dt)1/y$ does not tend to r as y tends to 0),

K is the carrying capacity,

p is the Pella-Tomlinson shape parameter,

α,β are the Walters shape parameters,

a,b,c are the Shepherd shape parameters,

M is the instantaneous rate of natural mortality,

μ is a shape parameter and

α_1,β_1 are recruitment-related parameters.

[In order to implement certain estimation procedures in exactly the same manner as described by Ludwig *et al.* (1988), the Ricker and Power functional forms have been altered so that the escapement biomass (the biomass at the beginning of a year, less the catch in that year) is used in the surplus production function instead of the biomass at the start of the year, y. This correction does not, however, apply to the "-y" term.

The choice of the most appropriate surplus production function for a stock is determined by how well this function fits the data and whether the data exhibit sufficient contrast to allow all the parameters to be estimated with reasonable precision. After fitting the Shepherd (1982) form to catch-effort data for the ICSEAF hake stocks, Butterworth and Andrew (1987b) observe that, although MSY is reasonably well determined, neither the corresponding stock level, MSYL, nor the related skewness parameter, c, can be well determined. Butterworth *et al.* (1986b) also report that, for the Schaefer-SQ form (which may be more flat-topped than the standard Schaefer form, although it also sets MSYL to K/2), the 95% confidence limits for μ do not differ from the case when $\mu = 2$ (corresponding to the Schaefer form) in all Divisions except Division 1.6.

3.7 Problems associated with the general production model

The general production model [equations (3.1) or (3.10)] makes several implicit assumptions which are unlikely to hold in practice:

1) The parameters of the model are time-invariant. It is probable that some of the parameter values will change systematically over the

history of the fishery - such variations can be expected as the fine structure of the population is altered by fishing, the more accessible subpopulations, for example, tending to be most heavily depleted. Some of the model parameters, such as the average pristine population (K), may vary systematically over time as a result of long term environmental changes.

2) The catchability coefficient, q, remains constant over the entire history of exploitation. Possible reasons why this is unlikely to be true in reality include :

(i) abnormally high catch rates in the early stages of exploitation caused by first fishing down the small areas of highest density (a possible explanation for the high initial cpue values recorded in all ICSEAF Divisions),

(ii) changes in mesh size which affect age-specific selectivity patterns (and hence the proportion of the total biomass corresponding to the exploitable biomass y),

(iii) an initial "learning" process as areas of higher density are discovered, which tends to reduce the effect described in (i),

(iv) inadequate allowance for changing vessel characteristics (i.e. inadequate power factors) and

(v) undetected increases/decreases in efficiency.

Butterworth and Andrew (1987b) illustrate that (for their model) an undetected increase in fishing efficiency due partly, perhaps, to changes in catchability, may result in an overestimate of up to 40% of the "true" predicted $Q_{0.1}$ value, while even parameters which are independent of current biomass such as MSY, tend to vary linearly as a function of an (undetected) increase in catching power. Attempts by these authors (Andrew and Butterworth 1988) to quantify suspected changes in q for the ICSEAF hake stocks as a result of mesh size changes have been unsuccessful, however, (except in Division 1.6) although they conclude that this may be possible with a larger data set.

3) The stocks are not substantially affected by emigration and immigration. Payne *et al.* (1988), however, notes that the hake stocks in Divisions 1.5 and 1.6 are closely related. The assumption that emigration and immigration effects are negligible is thus open to question. In most management situations, in addition to the problems associated with emigration and immigration, the substocks within the area assumed to be occupied by a stock may exhibit considerable fine structure (Walters 1986).

4) Fishing is a decidedly non-random operation with respect to spatial distribution. Accessible high density areas will always tend to be subjected to greater fishing intensities. The assumption that effort is randomly distributed over the fishing grounds may thus often be invalid and fish movement insufficiently rapid to compensate for this.

5) A linear relationship exists between cpue and stock density. This assumption has been questioned by Cooke (1985), who lists a number of scenario's in which cpue is more likely to be related to abundance by the power relationship:

$$(C/E)_i = (qy_t)^p \quad \text{where } p < 1 \tag{3.18}$$

Some of these are:

(i) effort calculations include those occasions on which q is zero (e.g. during bad weather),

(ii) effort calculations include the time spent steaming to the fishing grounds and handling the catch [Cooke (*op. cit.*) shows that even if this time is subtracted from the estimated effort, nonlinear relationships of the form of equation (3.18) still result because of fluctuations in catchability q],

(iii) searching is non-random,

(iv) stock density is not constant across the fishing grounds, and

(v) scouting vessels are used to locate areas of highest concentration.

In addition, serious statistical difficulties may arise when catch-effort data are fitted to the general production model. These include :

(i) Certain of the critical model parameters may be confounded, i.e. it is possible only to estimate a function of these parameters combined, rather than the actual individual parameter values, due to insufficient contrast in the data on stock size and fishing effort (Hilborn 1979).

(ii) Measurement error (e.g. error in recording the catch or effort) may disguise a *bona fide* relationship between variables so that they appear to be independent of each other [the "errors in variables" problem noted by Walters and Ludwig (1981)]. Even if this is not the case, measurement error may nevertheless bias parameter estimates substantially.

(iii) The precision of the estimates may not improve over time, as most management strategies aim to stabilise the biomass at some "optimum" level, thus having the effect of dampening out data contrast.

Table 3.1: Total catch and cpue data, and total effort estimates obtained therefrom, for the Cape hake stock in (a) Divisions 1.3. + 1.4, (b) Division 1.5, (c) Division 1.6 and (d) Divisions 2.1 + 2.2.

(a) Divisions 1.3 + 1.4

Year	Total catch (tons)	Cpue (OTB-7 tons/ hour fished)	Total effort (OTB-7 hours fished)
1965	93 510	1.78	52 534
1966	212 444	1.31	162 224
1967	195 032	0.91	214 321
1968	382 712	0.96	398 658
1969	320 430	0.88	364 125
1970	402 467	0.90	447 186
1971	365 557	0.87	420 180
1972	606 084	0.72	841 783
1973	377 642	0.57	662 530
1974	318 836	0.45	708 524
1975	309 374	0.42	736 605
1976	389 020	0.42	926 238
1977	276 901	0.49	565 104
1978	254 251	0.43	591 281
1979	170 006	0.40	425 015
1980	97 181	0.45	215 958
1981	90 523	0.55	164 587
1982	176 532	0.53	333 079
1983	216 181	0.58	372 726
1984	228 672	0.64	357 300
1985	211 450	0.66	320 378
1986	231 000	0.65	355 385
1987	223 000	0.63	353 968

Source: ICSEAF (1987)

(b) Division 1.5

Year	Total catch (tons)	Cpue (standardised units)	Total effort (standardised units)
1965	99 690	2.24	44 504
1966	122 183	2.62	46 635
1967	199 413	1.47	135 655
1968	247 680	1.38	315 133
1969	206 227	1.15	179 327
1970	224 731	1.10	204 301
1971	229 658	1.44	159 484
1972	214 026	1.00	214 026
1973	290 323	1.00	290 323
1974	195 722	0.70	279 603
1975	178 834	0.82	218 090
1976	212 025	0.58	365 560
1977	154 582	0.69	224 031
1978	125 139	0.56	223 462
1979	140 169	0.74	189 418
1980	74 667	0.71	105 165
1981	121 011	0.85	142 366
1982	130 546	0.84	155 412
1983	123 409	0.90	137 121
1984	141 968	0.92	154 313
1985	200 154	1.00	200 154
1986	176 200	0.92	191 522
1987	169 000	0.89	189 888

Source: ICSEAF (1987)

(c) Division 1.6

Year	Total catch (tons)	Cpue (ZAF tons/ std day)	Total effort (ZAF standard days)
1955	115 400	17.31	6 667
1956	118 200	15.64	7 558
1957	126 400	16.47	7 675
1958	130 700	16.26	8 038
1959	146 000	16.26	8 979
1960	159 900	17.31	9 237
1961	148 700	12.09	12 299
1962	147 600	14.18	10 409
1963	169 500	13.97	12 133
1964	162 300	14.60	11 116
1965	203 000	10.84	18 727
1966	195 000	10.63	18 344
1967	176 700	10.01	17 652
1968	143 600	10.01	14 346
1969	165 100	8.62	19 153
1970	142 500	7.23	19 710
1971	202 000	7.09	28 491
1972	243 933	4.90	49 782
1973	157 782	4.97	31 747
1974	123 000	4.65	26 452
1975	89 616	4.66	19 371
1976	143 894	5.35	27 018
1977	102 328	4.84	21 115
1978	101 140	5.90	17 312
1979	92 704	6.13	15 645
1980	101 538	5.48	18 554
1981	100 678	5.81	17 394
1982	85 970	5.87	14 779
1983	73 677	6.49	11 412
1984	86 407	6.67	12 467
1985	98 536	7.29	10 128
1986	108 370	6.97	11 425
1987	96 385	6.35	15 179

Source: (R. Leslie, pers. comm.)

(d) Divisions 2.1 + 2.2

Year	Total catch (tons)	Cpue (ZAF tons/ hour fished)	Total effort (ZAF standard hours)
1967	17 340	1.28	13 547
1968	31 370	1.28	24 508
1969	41 700	1.28	32 578
1970	27 800	1.22	22 787
1971	34 500	1.14	30 263
1972	51 388	0.64	80 294
1973	77 356	0.56	138 136
1974	100 909	0.54	186 869
1975	74 139	0.37	200 376
1976	57 974	0.40	144 935
1977	40 763	0.42	97 055
1978	39 239	0.41	95 705
1979	54 011	0.46	117 415
1980	47 692	0.44	108 391
1981	35 268	0.40	88 170
1982	47 262	0.51	92 671
1983	41 308	0.48	86 058
1984	43 340	0.55	78 800
1985	56 066	0.67	83 681
1986	50 340	0.63	79 905
1987	41 092	0.63	65 225

Source: ICSEAF (1987) and R. Leslie (pers. comm.)

4 MANAGEMENT STRATEGIES

4.1 Introduction

Any management process involves defining a policy, collecting information, making decisions and evaluating the results of these decisions (ACMRR 1979). In fishery management, decisions relating the inputs to the system, i.e the resources available (biomass, fishing vessels, etc.) to the outputs, i.e. the desired objectives (maximum profits and protein, etc.) should be based on scientific advice, the quality of which depends on the scientists' ability to assess accurately the state of a resource. This, in turn, requires substantial contrast in the data available on stock sizes and fishing effort (Hilborn 1979).

The objectives of the different parties involved in the management of fish resources often tend to be at variance. Factors which must be considered before making decisions include :

(i) catch - this should be as large as possible over an unlimited period (Babayan and Kizner 1988)

(ii) economic rent (profit) - the fishing industry requires profits for continued operation, and these are likely to be greatest if catches remain stable (to avoid the additional costs associated with fluctuations in production levels) and catch rates high

(iii) biomass - the probability of depleting the biomass below some critical level at which production by the resource would be substantially impaired (discussed further below) should be small

(iv) social and political goals - these, although important, are often very difficult to quantify and are therefore usually ignored by scientists when making management recommendations.

In many cases, one of the aims of a management agency may be to avoid "overexploitation". This term is not, however, well defined and suggested interpretations include (Walters 1986) :

(i) biological overexploitation - the biomass drops below that level which provides the maximum sustainable yield (MSY)

(ii) recruitment overexploitation - the spawning stock is reduced to a level at which the average recruitment is significantly diminished

(iii) economic overexploitation - either the net economic rent (profit) from the fishery is nil (or negative) or, more strictly, fishing effort is at a level above that which provides maximum economic rent

(iv) overcapacity - there is more capital/labour available in the fishery than is necessary to harvest the allowable catch (quota), or to realise the maximum economic yield.

The mathematical models employed to assess the dynamic state of the stock should be realistic and make reasonable demands on the available data. Although it is possible in principle to regulate the natural mortality (predation) of a species by culling its predators, there are many problems in attempting to quantify the predator-prey relationship [see, for example, problems encountered with attempts to rationalise the culling of Cape fur seals (Butterworth *et al.* 1988)]. Management strategies are thus usually designed to regulate either the fishing (as opposed to natural) mortality or the total catch.

4.2 Biological reference points

A biological reference point is defined as that biomass which corresponds to the equilibrium state of the resource (in the context of the deterministic approximation to the stochastic population dynamics equation for the resource) for a given management strategy. In the following, the equilibrium biomass or biological reference point associated with a particular management strategy R, will be referred to as y_R, the equilibrium catch as C_R, the corresponding equilibrium effort as E_R, and the quota required in year (n+1) in order eventually to stabilise the biomass at y_R as $Q_R(n+1)$. The sustainable yield from a resource is the annual catch which will leave the population at the end of any given year at the same level as at the start of that year (again in a deterministic dynamics context). The f_R strategy is designed so that if the population has been driven below (or above) y_R, applying a fixed level of fishing effort corresponding to this strategy will drive the biomass back to y_R. Strategies which employ catch quotas rather than effort restrictions can be similarly defined (see below).

The traditional aim of management programmes is to stabilise the population at that biomass (y_{MSY}) which provides the maximum sustainable yield (MSY) which is available under average environmental conditions. However, stabilising the biomass at y_{MSY} is not necessarily the most appropriate objective in the presence of environmental fluctuations (which lead to poor recruitment on occasions), as in "bad" years the biomass will drop below y_{MSY}, resulting in classification of the stock as "biologically overexploited"; this is particularly dangerous under a constant catch strategy, as maintaining a catch of MSY will continue to deplete the stock. Also, error in the estimation of y_{MSY} causes this strategy to stabilise the biomass at a level different from y_{MSY} (possibly resulting in biological overexploitation). Gulland and Boerema (1973) propose the $f_{0.1}$ strategy (an example of a general class of strategies called $f_{0.n}$ strategies) which, although not necessarily economically or biologically optimal, generally stabilises the biomass at a level greater than y_{MSY}, thus providing a hedge against the problems described above. In addition, steady state economic analysis of a fishery (discount rate $\delta = 0$ - see Section 4.3) results in an estimate of optimal effort which is smaller than E_{MSY} and which corresponds to a biomass in excess of y_{MSY}. There is one value of 0.n which results in the $f_{0.n}$ strategy providing true optimal effort (i.e. effort equal to the economically optimal effort); the data needed to calculate this value of 0.n are not usually available, but the $f_{0.1}$ strategy is adopted in the hope that this will adjust effort to a value closer to the optimal economic effort than, say, E_{MSY}.

Before defining the $f_{0.1}$ strategy, Gulland (1968) first outlines the concept of the marginal yield of a fishery. In Figure 4.1, the curve OACM is a general relation between equilibrium catch and effort. If the effort is increased from its initial level at E_1 to a new level, E_2, the equilibrium catch increases correspondingly by an amount BC. The efficiency of this increase (discrete marginal yield) is BC/BA. The marginal yield at E_1 is defined as the limit of the discrete marginal

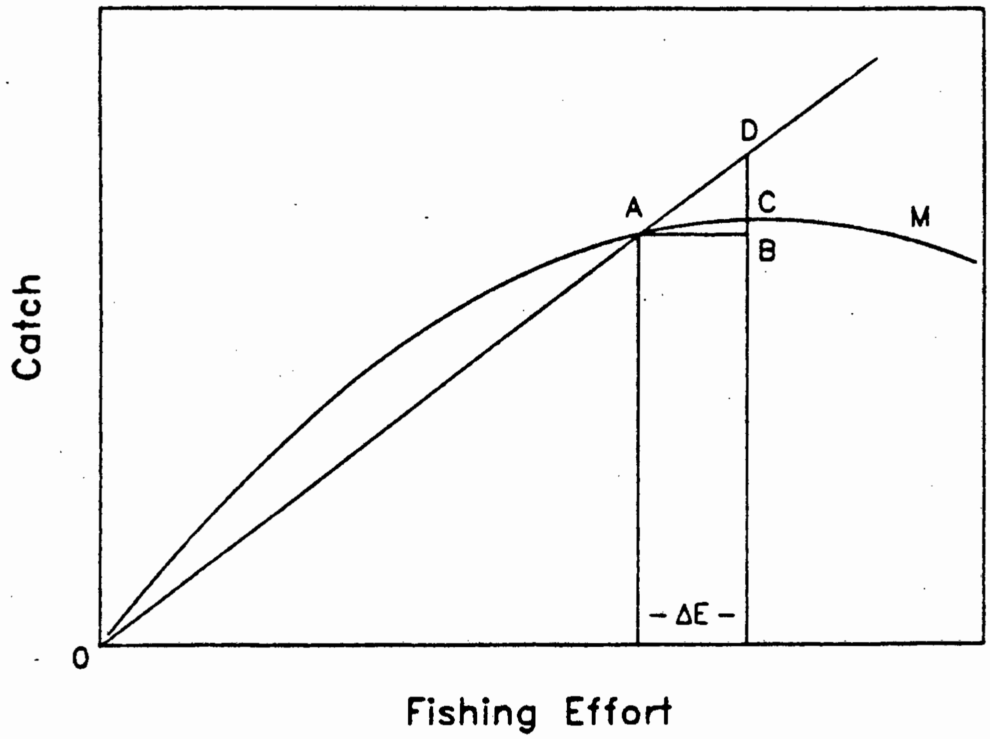


Figure 4.1: A general equilibrium relationship between catch and effort. BC represents the increase in equilibrium catch as fishing effort is increased from E_1 to E_2. The discrete marginal yield is the ratio BC/BA.

yield between E_1 and $(E_1 + \Delta E)$ as ΔE tends to zero. This limit is dC/dE, evaluated at E_1. The $f_{0.n}$ policy involves restricting fishing effort to that level at which the marginal yield has dropped to a fraction 0.n of its initial level (i.e. for the unexploited stock, this level corresponds to E = 0). This definition can be written as follows:

$$\left.\frac{dC}{dE}\right|_{E = E_{0.n}} = 0.n \left.\frac{dC}{dE}\right|_{E = 0} \tag{4.1}$$

The $f_{0.1}$ strategy proposed by Gulland and Boerema (1973) is a variant of the $f_{0.n}$ policy, with 0.n taken to be 0.1, and is currently in use by ICSEAF as their primary basis for setting catch quotas. Appendix 4.A. gives the formulae for quotas, equilibrium effort levels and biomasses corresponding to an $f_{0.n}$ strategy for some of the surplus production functions used in the estimation procedures described in Chapter 5.

4.3 Economic reference points

Fishery management should take into account those factors which influence the economic rent derivable from the resource. These include the sale price per unit mass of fish harvested, p, and the cost per unit of effort used in harvesting, c. In the simple analysis that follows, p and c are assumed to be constant. (In practice they are likely to be functions of both catch and time.)

Allowing the fishery to behave in an unregulated manner (i.e. no annual total catch quotas or effort restrictions are set) and using economic measures only, leads to an "open access" type of fishery which may be controlled to a degree by:

(i) entry taxes (license fees) which restrict the number of initial investments, but which may encourage overcapacity (Walters 1986)

(ii) operating taxes and subsidies which enable prices and costs to be adjusted so that the fishery yields maximum economic rent (to the community as a whole if not the fishermen/companies themselves) at some desirable biological reference point

(iii) restriction of new technology.

Clark (1976) proposes that fisheries management strategies be analysed in terms of the price/cost ratio and the discount rate δ, which is a measure of the relative importance of current compared to future revenues and hence catches, and thus allows for a quantitative comparison of high current catches with lower future returns, against lower current catches but higher future returns. Under the assumption that cpue is proportional to biomass, Clark's definition of the present value (PV) of a resource becomes :

$$PV = \int_0^{\infty} e^{-\delta t}[pqy - c]E \, dt \tag{4.2}$$

and he shows that the stock biomass $\tilde{y}$ which maximises the present value satisfies the relation :

$$\delta = g'(\tilde{y}) + \frac{g(\tilde{y}) / \tilde{y}}{q\tilde{y}p/c - 1} \tag{4.3}$$

where δ is the discount rate,

$g(y)$ is the surplus production function and

p/c is the ratio of prices to costs (assumed to be constant over all stock sizes and times), with p and c as defined above.

Butterworth *et al.* (1986b) suggest that for the hake stocks in the ICSEAF Convention Area, p/c may be assumed to be the inverse of the minimum catch rate recorded during the history of the fishery. The rationale for this is that during the mid-to-late 1970's (when catch rates were lowest), the local industry was effectively operating at zero net economic rent (Andrew and Butterworth 1987a). Butterworth *et al.* (1986b) conclude that use of the $f_{0.1}$ strategy (if this strategy is indeed optimal for the hake resources) corresponds to high discount rates which exceed the 5% recommended by Clark (1985) as being appropriate to conservation programmes.

4.4 Standard management strategies

The aim of most management strategies is to drive the current biomass y^* [indexed by the current cpue, $(C/E)^*$] to a biological (or economic) reference point, y_R. The most common policy is that of regulation by fixing fishing effort. This is known as the "constant effort strategy". A gradual (asymptotic) approach to y_R can be achieved by setting quotas according to the formula :

$$\begin{aligned} Q_R &= y^* \, g(y_R)/y_R \\ &= (C/E)^* \, E_R \end{aligned} \qquad (4.4)$$

where Q_R is the recommended quota and

$g(y_R)$ is the equilibrium yield corresponding to y_R.

For this strategy, y_R is a stable equilibrium point as long as g(y) is not depensatory in the region $[y_*, y_R]$, i.e. $g''(y) < 0$ in this interval. Beddington and May (1977) show by simulation that even when considerable environmental noise is present, this procedure will on average stabilise the population at y_R.

An alternative to the constant effort strategy is the "fixed escapement" strategy (Clark 1976, Walters 1986) by which quotas are set according to the formula :

$$Q_R = \begin{cases} y^* + g(y^*) - y_R & \text{if } y^* + g(y^*) > y_R \\ 0 & \text{otherwise} \end{cases} \qquad (4.5)$$

This strategy will effect a return to a biomass of y_R along the optimal pathway [for maximising PV (equation 4.2), for example]. It is unlikely to be acceptable to fishermen, however, due to the immediate large operating losses which may result from a complete halt to fishing after years of poor recruitment, for instance, during which the biomass falls below y_R.

The "constant quota" strategy involves setting a quota equal to C_R. Figure 4.2 illustrates how this method operates in a deterministic situation. If y^* is greater than y_{MSY}, the population stabilises at y_R. On the other hand, if y^* is less than y_{MSY}, the final equilibrium biomass depends on whether y^* is greater than y_{R1} or not; if it is, the biomass stabilises at y_R, but if not, it drops to extinction. If any environmental noise is present, this strategy will ultimately lead to extinction of the stock (Beddington and May 1977).

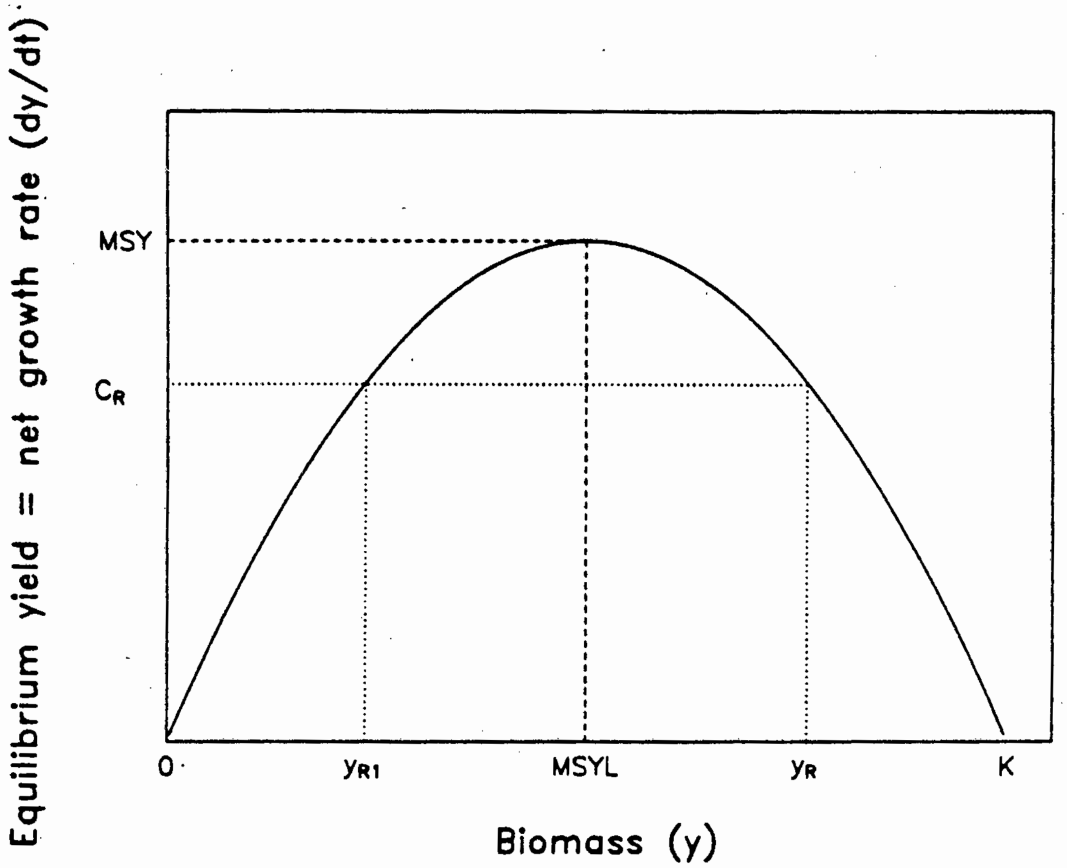


Figure 4.2: A surplus production curve illustrating the use of the constant catch strategy to stabilise the resource at y_R. For this strategy, there are two stable equibilria ($y = 0$ and $y = y_R$) and one unstable equilibrium ($y = y_{R1}$).

A compromise between the constant quota and constant effort strategies is the MAC (Maximum Allowable Catch) strategy (Butterworth 1987), which sets quotas according to the formula :

$$Q_R = \begin{cases} \dfrac{g(y_R)}{y_R} \; y^* & \text{if } y^* < y_R \\ g(y_R) & \text{otherwise} \end{cases} \tag{4.6}$$

Like the constant effort strategy, this strategy stabilises the population at y_R, but if $y^* > y_R$ the designated quota is held fixed at $g(y_R)$. [This strategy is similar to the "New Management Policy" for whale management (Allen 1976)]. The MAC strategy tends to reduce inter-annual quota fluctuations, as the MAC is independent of y^* if $y^* > y_R$, and is altered only on improvement in the estimates of $g(y_R)$ (i.e. when more data points become available). The precision with which the MAC can be determined is greater than that for the constant effort strategy quota, as y^* need not be estimated (although it must be known that $y^* > y_R$). As a result, this strategy should be more robust to model error.

The maximum effort strategy can be used if $y^* + g(y^*) > y_R$. This involves setting effort as high as possible until $y^* + g(y^*) = y_R$ and then harvesting the resource at $g(y_R)$. Although approaching the optimal solution for maximising PV in Clark's (1976) model, this strategy has serious limitations because an unregulated increase in effort encourages overcapacity. In addition, estimates of $g(y_R)$ and y^* during the declining phase of a fishery are usually biased and imprecise due to insufficient contrast in the fishing effort data (Hilborn 1979). This strategy corresponds to the optimum escapement strategy, except that even at maximum effort, it may not be possible to catch the maximum available catch $[y^* + g(y^*) - y_R]$.

4.5 Probing strategies

All of the management strategies discussed above are based on the policy of passive adaptation (i.e. treating the current "best" model as correct and waiting for natural fluctuations to reveal any model errors). These strategies have as their objectives the stabilisation of stock biomass at some desirable level dictated by certain (possibly *ad hoc*) criteria and determined by the currently available data. Because of the possibilities both of model errors and of imprecision in the model parameter estimates, such a policy may not necessarily be optimal, and occasional probing experiments should be considered as a means of detecting model error and improving parameter estimation precision, thereby ultimately improving resource utilisation. Such experiments involve making large relative changes in fishing effort in order to provide better estimates of the parameters and thus of the shape of the surplus production function. Experiments which produce only small disturbances are not likely to provide sufficient information to offset "wasted" yield. On the other hand, experiments should be designed so that the probability of seriously depleting the stock is low.

Walters (1984) suggests several scenario's in which probing rather than passive management strategies are appropriate. These include situations in which:

(i) the historical data (which may cover a wide range of stock sizes and are often critical to parameter estimation), are becoming less reliable due, perhaps, to effects such as changes in the "true" parameter values

(ii) large measurement errors are known to exist in the historical data set

(iii) there is insufficient contrast in the data, resulting in imprecise parameter estimates, which may lead to under- or overexploitation

(iv) the stock has high productivity, thus making any depletions caused by probing less serious

(v) an accurate monitoring system is available for recording responses to probing

(vi) maintenance of good (stable) catches now is not as important as avoiding low catches in the future (i.e. the discount rate is low).

Probing experiments may be used in conjunction with the strategies discussed above in order to update the shape of the yield function, and thus estimates of the target biomass, iteratively. The information gained from well designed experiments should, in the long term, more than compensate for any loss of current yield. Note that, as the number of such experiments increases, the marginal rise in present value will decrease until eventually, at some point which is dependent on the discount rate, the present value of the resource will fall. This is because the costs associated with such experiments (loss of catch, monitoring costs, etc.) will tend to reduce the PV of the resource. If the experiment is to be useful in maximising PV, the resultant (discounted) increase in revenue must exceed these costs. In a fishery with a high discount rate (i.e. in which current catches make up a large proportion of PV), any probing may reduce the PV of the resource.

4.6 Management strategy basis for this study

As ICSEAF's current policy is to use $f_{0.1}$ quotas as the basis for catch limit recommendations, the only management strategy which is considered in this study is the constant effort strategy. It is likely, however, that any estimation procedure which is able to estimate the parameters and variables required for this strategy accurately and precisely, will be able to estimate those quantities required for other management strategies with similar accuracy and precision.

In order to test a given management strategy in economic terms, values of the necessary economic parameters (such as prices and costs) are required. Currently these values are merely educated guesses, at best (see Andrew and Butterworth 1987a and Butterworth *et al.* 1986b), and consequently the analysis of management strategies involving economic criteria must wait until such data become available.

APPENDIX 4.A. EQUILIBRIUM BIOMASS, CATCH AND EFFORT LEVELS CORRESPONDING TO AN $f_{0.n}$ STRATEGY

The fishing effort corresponding to the $f_{0.n}$ strategy is that effort which satisfies the equation :

$$\left.\frac{dC}{dE}\right|_{E = E_{0.n}} = 0.n \left.\frac{dC}{dE}\right|_{E = 0} \tag{4.A.1}$$

The f_{MSY} strategy corresponds to $0.n = 0$ and the $f_{0.1}$ strategy to $0.n = 0.1$. Assuming equilibrium conditions and the linear observation model (equation 3.3), the rate of change of equilibrium catch with biomass (dC/dy) may be related to the rate of change of equilibrium catch with effort :

$$\frac{dC}{dE} = \frac{dC}{dy} \frac{dy}{dE} \tag{4.A.2}$$

Substituting (C/E)/q for y in equation (4.A.2) gives :

$$\frac{dC}{dE} = \frac{1}{q} \frac{dC}{dy} \frac{d(C/E)}{dE} \tag{4.A.3}$$

Now

$$\frac{d(C/E)}{dE} = \left[\frac{dC}{dE} E - C \right] \frac{1}{E^2}$$

so that substitution of qy for C/E (see equation 3.7) gives :

$$\frac{d(C/E)}{dE} = \left[\frac{dC}{dE} - qy \right] \frac{1}{E} \tag{4.A.4}$$

Substituting this result into equation (4.A.3) and multiplying by qE then gives :

$$qE \frac{dC}{dE} = \frac{dC}{dy} \left[\frac{dC}{dE} - qy \right] \tag{4.A.5}$$

Solving equation (4.A.5) for dC/dE :

$$\frac{dC}{dE} = \frac{qy \, . \, \frac{dC}{dy}}{\frac{dC}{dy} - qE} \tag{4.A.6}$$

and evaluating dC/dE at E = 0 (note that when E = 0, y = K) gives :

$$\left. \frac{dC}{dE} \right|_{E=0} = \frac{qK \, \frac{dC}{dy}}{\frac{dC}{dy} - q0}$$

$$= \quad qK \tag{4.A.7}$$

Now substituting the last two results into equation (4.A.1) gives:

$$\left. \frac{qy \, \frac{dC}{dy}}{\frac{dC}{dy} - qE} \right|_{E = E_{0.n}} = \quad 0.n \; qK$$

In all further analyses, y and E represent $y_{0.n}$ and $E_{0.n}$ respectively, and dC/dy is evaluated at $E_{0.1}$. Therefore :

$$qy \frac{dC}{dy} = 0.n \; qK \left[\frac{dC}{dy} - qE \right]$$

and dividing by q and substituting C/y for qE produces the result :

$$y \frac{dC}{dy} = 0.n \; K \left[\frac{dC}{dy} - \frac{C}{y} \right] \tag{4.A.8}$$

a) The Schaefer Surplus Production Function

The Schaefer surplus production model (see Chapter 3) relates equilibrium catch to biomass by the formula :

$$C = ry(1 - y/K) \qquad (4.A.9)$$

Taking the derivative of equation (4.A.9) with respect to y :

$$\frac{dC}{dy} = r(1 - y/K) - ry(1/K)$$

$$= r(1 - 2y/K) \qquad (4.A.10)$$

substituting equations (4.A.9) and (4.A.10) into equation (4.A.8) :

$$ry(1 - 2y/K) = 0.n\ K \left[r(1 - 2y/K) - r(1 - y/K) \right]$$

$$= 0.n\ K(-ry/K)$$

$$= -\ 0.n\ ry \qquad (4.A.11)$$

and dividing equation (4.A.11) by ry and solving for y produces the result :

$$y = K(1 + 0.n)/2 \qquad (4.A.12)$$

Replacing 0.n by 0 in equation (A.4.12) yields y_{MSY} = K/2 and equation (4.A.9) then gives MSY = rK/4. E_{MSY} is obtained from C/qy, which equals 0.5r/q. Setting 0.n to 0.1 in equation (4.A.12) gives $y_{0.1}$ = 0.55K = 1.10y_{MSY} and, by substitution into equation (4.A.9), $C_{0.1}$ = 0.99rK/4 = 0.99MSY and $E_{0.1}$ = 0.45r/q = 0.90E_{MSY}

b) The Fox Surplus Production Function

The Fox surplus production function (see Chapter 3) relates equilibrium catch to biomass by the formula :

$$C = ry[1 - \ln(y)/\ln(K)] \qquad (4.A.13)$$

Taking the derivative of equation (4.A.13) with respect to y :

$$\frac{dC}{dy} = r\left[1 - \frac{\ln(y)}{\ln(K)}\right] - \left[\frac{r\,y}{y\,\ln(K)}\right]$$

$$= r[1 - (\ln(y) + 1)/\ln(K)] \qquad (4.A.14)$$

substituting equations (4.A.13) and (4.A.14) into equation (4.A.8) :

$$ry\left[1 - \frac{\ln(y) + 1}{\ln(K)}\right] = 0.n\ rK\left[[1 - \frac{\ln(y) + 1}{\ln(K)}] - [1 - \frac{\ln(y)}{\ln(K)}]\right]$$

$$= 0.n\ rK/\ln(K)$$

and dividing by $r/\ln(K)$ produces the result :

$$y[\ln(K) - \ln(y) - 1] = 0.n\ K \qquad (4.A.15)$$

Replacement of 0.n by 0 in equation (4.A.15) gives $y_{MSY} = Ke^{-1} = 0.37K$ and, by substitution into equation (4.A.13), $MSY = rKe^{-1}/\ln(K)$ and $E_{MSY} = r/[q\ln(K)]$. Substituting 0.1 for 0.n and solving gives $y_{0.1} = Ke^{-0.7815}$, $C_{0.1} = 0.7815rKe^{-0.7815}/\ln(K) = 0.97MSY$ and $E_{0.1} = 0.7815r/[q\ln(K)] = 0.78E_{MSY}$

c) The Shepherd Surplus Production Function

The Shepherd surplus production function (see Chapter 3) relates equilibrium catch to biomass by the formula :

$$C = ay/(1+y/b) - My \qquad (4.A.16)$$

Taking the derivative of equation (4.A.24) with respect to y gives :

$$\frac{dC}{dy} = \frac{a}{(1+y/b)^2} - M \qquad (4.A.17)$$

Substituting equations (4.A.16) and (4.A.17) into equation (4.A.8) :

$$\frac{ay}{(1+y/b)^2} - My = 0.n\ K \left[\frac{a}{(1+y/b)^2} - \frac{a}{(1+y/b)} \right]$$

$$= 0.n\ K \left[\frac{-ay/b}{(1+y/b)^2} \right] \qquad (4.A.18)$$

multiplying by $(1+y/b)^2$:

$$ay - My(a+y/b)^2 = 0.n\ K\ (-ay/b) \qquad (4.A.19)$$

and dividing by y and solving, produces the result :

$$y = b[\ (a(1+0.nK/b)/M) - 1] \qquad (4.A.20)$$

Setting 0.n = 0 in equation (4.A.20) gives $y_{MSY} = b[\ (a/M) - 1]$. Results for other values of 0.n may be obtained by first solving (4.A.20).

d) The Ricker Surplus Production Function

The Ricker surplus production function and the non-linear observation model relate equilibrium catch, biomass and effort by the equations :

$$y = (y - C)\, e^{\alpha - \beta(y - C)} \qquad (4.A.21)$$

$$C = y\,(1 - e^{-qE}) \qquad (4.A.22)$$

Subtracting both sides of equation (4.A.22) from y gives :

$$y - C = y\, e^{-qE} \qquad (4.A.23)$$

Substituting equation (4.A.23) into equation (4.A.21) and dividing by y then gives :

$$1 = e^{-qE}\, e^{\alpha - \beta(ye^{-qE})} \qquad (4.A.24)$$

Taking the natural logarithm of equation (4.A.24) and adding qE to both sides yields :

$$qE = \alpha - \beta(ye^{-qE})$$

and substituting (4.A.22) for y in this equation and simplifying then gives :

$$\frac{\beta C}{e^{qE} - 1} = \alpha - qE \qquad (4.A.25)$$

Solving for C produces the result :

$$C = \frac{1}{\beta} (\alpha - qE).(e^{qE} - 1) \tag{4.A.26}$$

Taking the derivative of equation (4.A.26) with respect to E :

$$\frac{dC}{dE} = \frac{-q}{\beta} (e^{qE} - 1) + \frac{q}{\beta} (\alpha - qE)e^{qE} \tag{4.A.27}$$

and setting E to zero in this equation gives :

$$\left.\frac{dC}{dE}\right|_{E = 0} = \frac{q\alpha}{\beta}$$

The equilibrium effort corresponding to the $f_{0.n}$ strategy is thus obtained by solving for E in the equation :

$$(\alpha - qE).e^{qE} - (e^{qE} - 1) = 0.n\alpha$$

e) The Power Surplus Production Function

The Power surplus production function and the non-linear observation model relate equilibrium catch, biomass and effort by the equations :

$$y = e^{\alpha} (y - C)^{\beta} \tag{4.A.28}$$

$$C = y\,(1 - e^{-qE}) \tag{4.A.29}$$

Subtracting both sides of equation (4.A.29) from y gives :

$$y - C = y\, e^{-qE} \tag{4.A.30}$$

Substituting equations (4.A.29) and (4.A.30) into equation (4.A.28):

$$\frac{C}{(1 - e^{-qE})} = e^{\alpha} \left[\frac{C\, e^{-qE}}{(1 - e^{-qE})}\right]^{\beta} \tag{4.A.31}$$

and dividing by $C/(1 - e^{-qE})$ gives :

$$1 = e^{\alpha - q\beta E} \left[\frac{C}{(1 - e^{-qE})}\right]^{\beta - 1} \tag{4.A.32}$$

Solving for C then gives :

$$C = e^{(q\beta E - \alpha)/(\beta - 1)} (1 - e^{-qE}) \tag{4.A.33}$$

Taking the derivative of equation (4.A.33) with respect to E :

$$\frac{dC}{dE} = \left[\frac{q\beta}{\beta - 1} (1 - e^{-qE}) + qe^{-qE}\right] e^{(q\beta E - \alpha)/(\beta - 1)} \tag{4.A.34}$$

and setting E to zero in this equation gives

$$\left.\frac{dC}{dE}\right|_{E=0} = q\ e^{-\alpha/(\beta-1)} \tag{4.A.35}$$

The equilibrium effort corresponding to the $f_{0.n}$ strategy is thus obtained by solving for E in the equation :

$$\left[\frac{q\beta}{\beta - 1}(1 - e^{-qE}) + qe^{-qE}\right] e^{q\beta E/(\beta-1)} = 0.nq \tag{4.A.36}$$

5 MODEL ESTIMATION PROCEDURES INVESTIGATED

5.1 Introduction

Various forms of the general surplus production model have been proposed for the management of the hake stocks in the ICSEAF Convention Area. In what follows, the term "model" will be used to denote any description of the stock or cpue dynamics. A "model estimation procedure" (or "estimation" procedure) is the method used to estimate the model parameters. For this reason, many estimation procedures may correspond to the same single model. In order to illustrate how well the different estimation procedures perform, they are (where possible) first applied assuming an observation error structure and subsequently assuming a process error structure, using ℓn(cpue) minimisation :

$$SS = \sum_{i=1}^{n} w_i[\ell n(C/E)_i - \ell n(\widehat{C/E})_i]^2 \qquad (5.1)$$

where $(C/E)_i$ is the observed (or artificially generated) cpue for year i,

$(\widehat{C/E})_i$ is the model-predicted cpue for year i and

w_i is the weight assigned to the data point for year i (set to 1 for all calculations in this study).

Using only ℓn(cpue) minimisation allows comparison of the performance of the estimation procedures without confounding of the results by differences corresponding only to the use of different minimisation criteria (see Butterworth and Andrew 1987a). The choice of ℓn(cpue) minimisation is in accordance with the recommendations of Butterworth and Andrew (*op. cit.*), which were based primarily on work by de la Mare (1984,1986).

For those models which can be formulated as observation error estimators, two variants are considered :

i) fixing y_1 = K [where K is the (average) biomass of the unexploited resource]

ii) treating y_1 as an estimable parameter.

In case (ii), an additional parameter (y_1) must be estimated.

For models which can be formulated as process error estimators, three possible methods of estimating the (average) cpue for the unexploited resource (α = qK) are considered :

a) α is estimated simultaneously with the other parameters, using a single (usually non-linear) optimisation

b) α is estimated by $(C/E)_1$ (the first cpue value in the data set)

c) α is estimated by extrapolating the first five cpue data points (years i = 1 to 5) back to year 0.5 using linear regression. $(C/E)_{0.5}$ corresponds to an estimate of the cpue when the stock was unexploited, because the relation for cpue in year i can be written :

$$(C/E)_i = q\left(\frac{y_i + y_{i+1}}{2}\right)$$

which corresponds approximately to

$$qY_{i+1} = [(C/E)_i + (C/E)_{i+1}]/2$$

so that

$$qY_1 = qK = [(C/E)_0 + (C/E)_1]/2 = (C/E)_{0.5}$$

[Note that b) and c) assume, as does i) for observation error estimators, that the available cpue data series begins when exploitation of the stock commenced, and that the stock was at that time at its average unexploited equilibrium biomass. This is the situation for the Butterworth age-structured operating model, and would seem also to be a reasonable assumption for the cpue series available for the ICSEAF hake stocks. These procedures would be less defensible for other situations, e.g. a stock already substantially depleted at the time the cpue data series commenced, and the results of this study do not necessarily translate to such scenarios'.]

For observation error estimators, cpue in year i is assumed to be proportional to average biomass during that year :

$$(C/E)_i = q(\frac{Y_i + Y_{i+1}}{2})$$

A nearly equivalent formulation for process error models can be obtained by substituting :

$$Y_{i+1} = [(C/E)_i + (C/E)_{i+1}]/(2q)$$

into the dynamic production model equation. However, this produces some rather messy algebra requiring implicit equation solution in many cases, so that the easier route of substituting :

$$y_i = (C/E)_i/q$$

into the dynamic production model equation instead, has been chosen.

Following the suggestion of Babayan and Kizner (1988), all models which can be transformed into process error estimators are implemented using both smoothed and unsmoothed cpue data. Smoothing has been shown to produce more accurate estimates from a process error estimator in the case of a whale management algorithm (Punt and Butterworth 1988). Observation error estimators are not implemented using smoothed cpue data, following indications in Butterworth (1988c) which suggest that pre-smoothing of cpue data for use by observation error estimators is unlikely to improve variable and parameter estimates. The technique of Mohn (1980) is used to smooth the cpue data:

$$(C/E)_1^s = 2/3(C/E)_1 + 1/3(C/E)_2$$

$$(C/E)_i^s = \frac{1}{4}(C/E)_{i-1} + \frac{1}{2}(C/E)_i + \frac{1}{4}(C/E)_{i+1} \qquad (2 \le i \le n-1) \qquad (5.2)$$

$$(C/E)_n^s = 1/3(C/E)_{n-1} + 2/3(C/E)_n$$

In summary, each model is formulated (in so far as is possible) to provide eight estimation procedures as follows :

1) observation error estimator, $y_1 = K$
2) observation error estimator, y_1 estimated
3) process error estimator, unsmoothed data, α (=qK) estimated [i.e. a) above]
4) process error estimator, unsmoothed data, $\hat{\alpha} = (C/E)_1$ [i.e. b) above]

5) process error estimator, unsmoothed data, α estimated using the linear regression with time method [i.e. c) above]

6) process error estimator, smoothed data, α (=qK) estimated [i.e. a) above]

7) process error estimator, smoothed data, $\hat{\alpha} = (C/E)_1^s$ [i.e. b) above]

8) process error estimator, smoothed data, α estimated using the linear regression with time method [i.e. c) above].

Where possible, each procedure is applied to the data using both the Schaefer and Fox forms of the surplus production function g(y) (although in principle any of the other forms suggested in the scientific literature could be used). For consistency with the suggestion of Butterworth and Andrew (1984) , the parameters included in the non-linear minimisation search are r (or an alternative for models which do not include this parameter, e.g. μ in the case of the Lleonart *et al.* model), MSY and qK [qK is pre-assigned when cases (b) and (c) for process error estimators are implemented]. These parameters have been chosen because r and K have been found to be negatively correlated (Butterworth and Andrew *op. cit.*). For observation error estimators, q is estimated without being included in the non-linear search [see Appendix 5.A for a description of this technique when ℓn(cpue) minimisation is used], except in the case of the observation error form of the Lleonart *et al.* model, where q appears in the effective surplus production function. In order to ensure that the parameters obtained from the non-linear search are biologically reasonable, these parameters are constrained so that they remain positive.

The following symbols appear in the equations below :

y_i - the biomass at the beginning of year i,

C_i - the catch reported in year i,

E_i - the fishing effort applied in year i,

g(y) - the surplus production function [written $\tilde{g}(E)$ as a function of fishing effort for an equilibrium situation] and

q - the catchability coefficient.

5.2 The Babayan *et al.* Time Series methods (Babayan *et al.* 1985, 1986, 1987, 1988)

A number of approaches involving the extrapolation of cpue time series have been suggested by these authors. All are based on determination of quotas according to the formula :

$$\hat{Q}_{0.n}(n+1) = \widehat{(C/E)}_{n+1} \hat{E}_{0.n} \tag{5.3}$$

$\widehat{(C/E)}_{n+1}$ and $\hat{E}_{0.n}$ are estimated "independently", $\hat{E}_{0.n}$ using Gulland's (1961) functional regression method (see below) and $\widehat{(C/E)}_{n+1}$ by a variety of methods for the extrapolation of the time series of cpue values.

Mendelssohn (1981) and Saila *et al.* (1980) have shown that the Box-Jenkins (1976) type of time series methods may, in certain circumstances, be used successfully for prediction of future cpue values [over a short time period (1-2 years)] if the $(C/E)_i$ series is a realisation of a stationary time series. However, the use of these methods to describe the cpue dynamics allows only "the determination of trends in stock dynamics, without revealing the cause-effect relationship of the process" (Babayan and Kizner 1988).

Certain of the time series approaches described below do not make use of data from the initial period of exploitation. The reason for this (Babayan and Kizner *op. cit.*) is that "quite accurate reproduction of the stock-fishery system can be obtained for the remaining years of the series if these points are omitted".

a) The Linear Method (Babayan *et al.* 1986)

If the cpue series shows a constant trend over the recent past which is expected to remain throughout the forecasting period, $(C/E)_{n+1}$ may be estimated by extrapolating a linear fit to the cpue time trend since an appropriate time [1976 being selected here by Babayan *et al* (1986) as appropriate to the start of the upward trend for the cpue series in Divisions 1.3 + 1.4 over recent years].

b) The Combined Brown Method (Brown 1963, Babayan *et al.* 1986)

This method models the time series of the last 6 cpue data points, using exponential smoothing with smoothed coefficients. The algorithm used to estimate the parameters and to predict cpue is given in Appendix 5.B.

c) The Exponential Smoothing Method (Babayan *et al.* 1988)

The algorithm used to predict cpue and to estimate the model parameters is given in Appendix 5.C. Babayan *et al.* (1988) also suggest two other, similar methods based on this approach, for predicting cpue.

d) The AR(m) Method

This method [called the Maximum Entropy Method by Babayan *et al.* (1985)] models cpue as follows :

$$\widehat{(C/E)}_i = p_1(C/E)_{i-1} + p_2(C/E)_{i-2} + \ldots + p_m(C/E)_{i-m} \qquad (5.4)$$

where the parameters p_1 .. p_m are estimated by minimising the functional :

$$SS = \sum_{i=m+1}^{n} [(C/E)_i - \widehat{(C/E)}_i]^2 \qquad (5.5)$$

[The parameters $\{p_i\}$ (for specified m) are estimated using multilinear regression.] In order to determine the number of parameters (m), the largest value of m is assumed to be 6 and the parameters p_1 .. p_6 are estimated. The model is then fitted with successively fewer parameters and the fit tested each time [using the asymptotic log-likelihood ratio test (Draper and Smith 1966)] to determine whether it is significantly different at the 5% level from the fit with one additional parameter. The parameters estimated for the model fit with the lowest number of parameters (which is not significantly different from all fits with more parameters) are used.

e) The ARIMA Method

The cpue dynamics are modelled as follows :

$$\widehat{(C/E)}_i = \theta_{i-1} + \theta_{i-2} + \theta_{i-3} + \phi_1(C/E)_{i-1} + \phi_2(C/E)_{i-2} + \phi_3(C/E)_{i-3} \qquad (5.6)$$

where θ_1, θ_2 and θ_3 are zero,

$\theta_k = (\widehat{C/E})_k - (C/E)_k$ for $k > 3$ and

ϕ_1, ϕ_2, ϕ_3 are the autoregressive parameters.

The parameters of this model are estimated by minimising the functional:

$$SS = \sum_{i=4}^{n} [(C/E)_i - (\widehat{C/E})_i]^2 \qquad (5.7)$$

5.3 The Babayan-Kizner model (Babayan and Kizner 1988)

The fishery is modelled as follows :

$$\begin{aligned} \hat{y}_{i+1} &= y_i + g(y_i) - C_i \\ y_i &= [(C/E)_i + (C/E)_{i-1}]/2q \end{aligned} \qquad (5.8)$$

The model parameters are estimated by assuming pure process error and minimising the functional :

$$SS = \sum_{i=2}^{n-1} [\ell n(qy_{i+1}) - \ell n(q\hat{y}_{i+1})]^2 \qquad (5.9)$$

$(\widehat{C/E})_{n+1}$ is estimated from the equation :

$$(\widehat{C/E})_{n+1} = (C/E)_{n-1} + 2qg[\{(C/E)_n + (C/E)_{n-1}\}/2q] - 2qC_i$$

5.4 The Butterworth-Andrew model (Butterworth and Andrew 1984)

The fishery is modelled as follows :

$$y_{i+1} = y_i + g(y_i) - C_i$$

$$\widehat{(C/E)}_i = q\left(\frac{y_{i+1} + y_i}{2}\right) \tag{5.10}$$

Quotas are estimated according to the formula :

$$\hat{Q}_{0.n} = \widehat{(C/E)}_n \hat{E}_{0.n}$$

The procedure uses $\widehat{(C/E)}_n$ rather than $\widehat{(C/E)}_{n+1}$ (which would also require a value of C_{n+1} for estimation) for consistency with earlier ICSEAF procedures (Butterworth and Andrew 1987a). This is an adequate approximation if the stock biomass is unlikely to change substantially over the coming year. [As the current ICSEAF policy is to stabilise the the hake stock biomasses at their $f_{0.1}$ equilibrium level, and the Butterworth-Andrew procedure estimates most stocks to be already close to this level, the approximation seems reasonable and should become more accurate with time.] For those procedures in which the model is transformed to a process error estimator, y_i is replaced by $(C/E)_i/q$ to give :

$$\widehat{(C/E)}_{i+1} = (C/E)_i + qg[(C/E)_i/q] - qC_i$$

In order to use the TLS method of estimation, it is assumed that equations (5.10) have error structure :

$$y_{i+1} = (y_i + g(y_i))e^{w_i} - C_i$$

$$\widehat{(C/E)}_i = q\left(\frac{y_{i+1} + y_i}{2}\right)e^{v_i}$$

The process errors $\{w_i\}$ are estimated as follows :

1) y_{i+1} is estimated by $(2/q)(C/E)_i e^{-\hat{v}_i} - \hat{y}_i$. The start $(\hat{y}_1)$ of the estimated biomass series is set to $\hat{K}$ if $y_1 = K$, or otherwise regarded as a parameter in the non-linear optimisation search.

2) $\hat{w}_i$ is estimated by $\ell n\{(\hat{y}_{i+1} - C_i)/(\hat{y}_i - g(\hat{y}_i)\}$.

5.5 Gulland's (Functional) Regression (Gulland 1961)

This method involves estimating the parameters of the surplus production function g(y) without the use of a dynamic model, but also without explicitly making the continuous equilibrium assumption. The method assumes that current cpue can be related to fishing effort averaged over the preceding T years, where T is the average period over which a year class is harvested by the fishery, i.e. the averaged effort is defined as :

$$\bar{E}_i = \frac{1}{T} \sum_{j=i-T+1}^{i} E_j \qquad (5.11)$$

The parameters of the surplus production function (and hence some of the management parameters) are calculated using Geometric Mean (i.e. Functional) regression (Ricker 1975) in this application, as has been customary at ICSEAF.

5.6 The Horbowy-Draganik model (Horbowy and Draganik 1988)

The rate of change of biomass is modelled by the continuous Pella-Tomlinson (Pella and Tomlinson 1969) surplus production function :

$$\frac{dy}{dt} = ry(1 - (y/K)^{n-1}) - qEy \qquad (5.12)$$

where r is the intrinsic growth rate,

K is the carrying capacity,

q is the catchability coefficient and

n is a shape parameter.

The Fletcher (1978a,b) reconstruction of (5.12) is :

$$\frac{dy}{dt} = \Upsilon m(\frac{y}{K}) - \Upsilon m(\frac{y}{K})^{n} - qEy \qquad (5.13)$$

where m is the maximum sustainable yield (MSY) and

Υ is the numerical factor $n^{n/(n-1)}/(n-1)$.

It can be shown that (5.13) may be integrated to give :

$$\hat{y}_{i+1} = [\{y(E_i)_*\}^{1-n} + U.\exp\{(\Upsilon m/K - qE_i)(1-n)\}]^{1/(1-n)} \qquad (5.14)$$

where E_i is the constant rate of effort during year i,

$y(E_i)_*$ is the equilibrium biomass corresponding to this constant effort :

$$y(E)_* = \left(\frac{\Upsilon m}{\Upsilon m - qEK}\right)^{1/(1-n)} K$$

U is the constant of integration :

$$U = \{y_i\}^{1-n} - \{y(E_i)_*\}^{1-n}$$

The parameters (n,q,m,K) are estimated by minimising the functional :

$$SS = \sum_{i=1}^{n} (C_i - \hat{C}_i)^2/\hat{C}_i^2$$

where $\hat{C}_i = q E_i \hat{y}_i$, using non-linear optimisation. In order to estimate quotas, the formula used is :

$$\hat{Q}_{0.n}(n+1) = \widehat{(C/E)}_n \, \hat{E}_{0.n}$$

Horbowy and Draganik (*op. cit.*) extend their estimation procedure to utilise VPA biomass estimates in the fitting procedure. This extension is, however, beyond the scope of this study and has thus not been implemented here.

5.7 The Lleonart *et al.* model (Lleonart *et al.* 1985a)

This model is based on the concept of the inertia of a stock. Inertia is defined (Lleonart *et al.* 1985a) as the stock's resistance, per unit time, to adapt to a new exploitation pattern. The reasoning behind this is that the effect of age-structure should be the prevention of instantaneous changes in biomass (and hence cpue) with variation in effort and thus fishing mortality. The cpue dynamics are modelled as follows :

$$\widehat{(C/E)}_i = (1-\mu)\ \tilde{g}(E_i)/E_i + \mu (C/E)_{i-1} \qquad (5.15)$$

where $\widehat{(C/E)}_i$ is the predicted cpue in year i,

$(C/E)_i$ is the observed cpue in year i,

E_i is the effort in year i,

$\tilde{g}(E_i)$ is the equilibrium yield corresponding to E_i and

μ is the inertia.

The incorporation of the $\mu(C/E)_{i-1}$ term allows the model to have a "memory", the strength of which is determined by the value of μ. When μ = 0 (no inertia), the stock moves immediately to the new equilibrium state under the imposition of effort E. When μ = 1 (high inertia), the change of effort does not effect the stock and the cpue remains as it was the previous year. The actual value of μ (between 0 and 1) represents the relative balance between these two extremes.

Quotas for this procedure are calculated by the formula :

$$\hat{Q}_{0.n}(n+1) = (1-\hat{\mu})\ \tilde{g}(\hat{E}_{0.n}) + \hat{\mu}(C/E)_n\ \hat{E}_{0.n} \tag{5.16}$$

In order to transform the above estimation procedure (implicitly a process error model) into an observation error estimator, $(C/E)_i$ is replaced by qy_i in equation (5.15) to give :

$$qy_i = (1-\mu).\tilde{g}(E_i)/E_i + \mu qy_{i-1} \tag{5.17}$$

Dividing (5.17) by q and replacing E_i by C_i/qy_i then gives :

$$y_i = \frac{(1-\mu)y_i}{Ci}\ \tilde{g}(C_i/qy_i) + \mu y_{i-1} \tag{5.18}$$

Non-linear solution of equation (5.18) is required in order to estimate y_i, given y_{i-1} and C_i. The expected cpue (following the example of the Butterworth-Andrew procedure) is then modelled by :

$$\widehat{(C/E)}_i = q(\frac{y_{i+1} + y_i}{2}) \tag{5.19}$$

and quotas are set according to the formula :

$$\hat{Q}_{0.n} = \widehat{(C/E)}_n \hat{E}_{0.n}$$

5.8 The Ricker and Power models (Ludwig *et al.* 1988)

These models of the resource dynamics, together with the non-linear observation model, may be written :

$$y_{i+1} = (y_i - C_i)e^{a_1 - b_1(y_i - C_i)} \quad \text{[Ricker]}$$

$$y_{i+1} = e^{a_2}(y_i - C_i)^{b_2} \quad \text{[Power]}$$

$$\hat{C}_i = y_i \ (1 - e^{-qE_i})$$

The model parameters are estimated using the TLS method (see Section 3.4) where here the assumption is made of equal observation and process error variances [$\sigma_v = \sigma_w$; $\lambda = 1/2$ - see equation (3.16)]. Quotas are estimated according to the formula :

$$\hat{Q}_{0.n} = \widehat{(C/E)}_n \hat{E}_{0.n}$$

5.9 The Deriso and Schnute-85 model (Schnute 1985)

The delay difference models of Deriso (1980) and Schnute (1985) incorporate age-structure effects and treat each component of production and mortality individually. Some of the parameters of these models have a specific biological interpretation [and auxiliary information can therefore be used to validate (or invalidate) them]. In order to reduce the number of estimable parameters when auxiliary information is available, this information can be explicitly incorporated into the model by setting each of the parameters concerned to its auxiliary estimate. [This is the same as adding the additional term $w(p - \hat{p})^2$ to the minimisation criterion, where $w \to \infty$ and p is a parameter for which auxiliary information is available in the form of the estimate $\hat{p}$. (Taking $w \to \infty$ corresponds to assuming that this parameter is estimated exactly from the auxiliary information.)]

From a plot of hake mass against age (Fig. 5.1), it can be seen that mass (for age > 3) is well represented by the linear model:

$$w_a = \alpha + \beta a$$

where w_a is the mass at age a. A delay difference relation for mass (for age > 3) relates the masses at different ages by the equation :

$$w_{a+1} = 2w_a - w_{a-1}$$

This relation corresponds to the Brody form used by Deriso (1980) and Schnute (1985) :

$$w_{a+1} = (1+\rho)w_a - \rho w_{a-1} \qquad (5.20)$$

where $\rho = 1$.

Deriso (1980) defines the exploitable biomass (y_i) as :

$$y_i = \sum_{a=k}^{\infty} N_{a,i}\, w_a \qquad (5.21)$$

where y_i is the exploitable biomass at the beginning of year i,

$N_{a,i}$ is the number of fish aged a at the beginning of year i and

w_a is the average mass of an individual fish aged a.

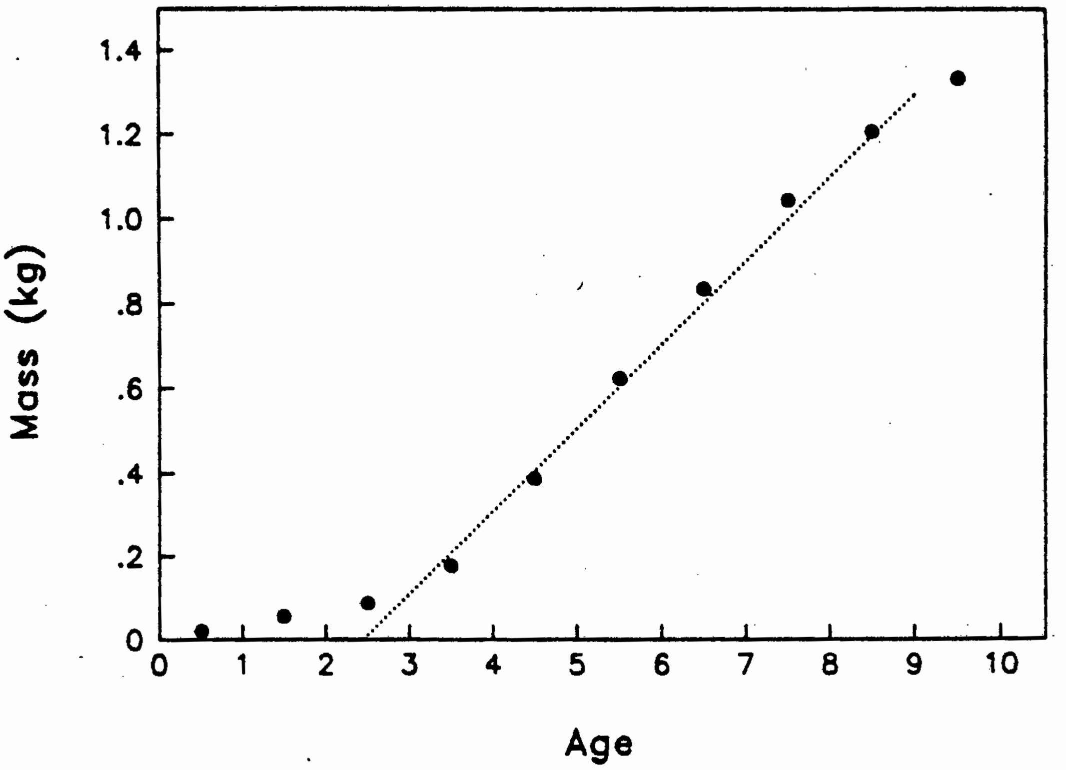


Figure 5.1: A plot of mass of hake against age (see Table 7.1), showing the linear approximation to mass-at-age for ages greater than three years.

Equation (5.21) assumes that all fish aged k and older have been recruited into the fishery, with the exclusion of all younger fish (the "knife-edge" selectivity assumption). [Deriso (1980) also describes a variation of his model in which a "pool" of young fish is used, rather than knife-edged selectivity, but for simplicity this is not considered here.] Because it can be assumed that few adults attain the maximum physiologically possible age (Deriso *op. cit.*), the summation in equation (5.21) is extended to age infinity instead of being truncated, as this should make little quantitative difference to the results.

Now if all exploitable fish experience the same rate of annual survival in year i, τ_i, the number of fish aged (k+1) and older in year (i+1) can be related to the number in year i and to the number of incoming recruits by the equation :

$$\sum_{a=k}^{\infty} N_{a,i+1} = \sum_{a=k}^{\infty} \tau_i \; N_{a,i} + R_{i+1} \tag{5.22}$$

where R_{i+1} is the number of recruits during year i which were not at the time vulnerable to fishing, but which are present in the exploitable biomass in year (i+1) and

$\sum_{a=k}^{\infty} \tau_i \; N_{ai}$ represents the number of adult (exploitable) fish surviving from year i to year (i+1).

Multiplying (5.20) by $N_{a+1,i+1}$ and rearranging terms gives :

$$N_{a+1,i+1} \cdot w_{a+1} = (1+\rho) . N_{a+1,i+1} \cdot w_a - \rho . N_{a+1,i+1} \cdot w_{a-1} \tag{5.23}$$

and replacing $N_{a+1,i+1}$ by $(N_{a,t} \cdot \tau_i)$ in the first term and by

$N_{a-1,i-1} \cdot \tau_{i-1} \cdot \tau_i$ in the second term on the RHS of equation (5.23) gives:

$$N_{a+1,i+1} \cdot w_{a+1} = (1+\rho) . N_{a,t} \cdot \tau_i \cdot w_a - \rho . N_{a-1,i-1} \cdot \tau_i \cdot \tau_{i-1} \cdot w_{a-1} \qquad a \geq (k+1)$$

(5.24)

$$(1+\rho) . N_{a,i} \cdot \tau_i \cdot w_a - \rho . N_{a-1,i-1} \cdot \tau_i \cdot e^{-M} . w_{a-1} \qquad a = k$$

Summing the terms in equation (5.24) from k to infinity :

$$\sum_{a=k}^{\infty} N_{a+1,i+1} \cdot w_{a+1} = (1+\rho) . \sum_{a=k}^{\infty} N_{a,i} \cdot \tau_i \cdot w_a - \rho \sum_{a=k+1}^{\infty} N_{a-1,i-1} \cdot \tau_i \cdot \tau_{i-1} \cdot w_{a-1}$$

$$- \rho . N_{k-1,i-1} \cdot \tau_i e^{-M} w_{k-1} \qquad (5.25)$$

and substituting for the summations [from equation (5.22)] gives :

$$y_{i+1} - w_k . R_{i+1} = (1+\rho) . y_i \cdot \tau_i - \rho \cdot \tau_i \cdot \tau_{i-1} \cdot y_{i-1} - \rho \cdot \tau_i . R_i \cdot w_{k-1} \qquad (5.26)$$

Re-arrangement of equation (5.26) then produces the basic Deriso-Schnute model:

$$y_{i+1} = y_i \cdot (1+\rho) \cdot \tau_i - \rho \cdot \tau_i \cdot \tau_{i-1} \cdot y_{i-1} - \rho \cdot \tau_i . R_i \cdot w_{k-1} + R_{i+1} \cdot w_k$$

It now remains to specify functional forms for τ_i and R_{i+1}. The recruitment in numbers in year i, R_i, depends on the number of mature adults k years before (as each individual takes k years to recruit into the fishery). Assuming that the age at recruitment into the fishery is the same as the age of maturity, the number of live births in year i, $N_{0,i}$, can be modelled by a generalised Beverton-Holt stock-recruitment relation :

$$N_{0,i} = \frac{a y_i}{(ab + y_i)^{\gamma}} \qquad (5.27)$$

Converting this to the biomass being recruited to the fishery in year i requires allowing k years of natural mortality and multiplying by w_k (the weight of an individual fish aged k years old). The recruiting biomass is thus :

$$w_k.R_i = \frac{w_k.a.e^{-Mk}.y_{i-k}}{(ab + y_{i-k})^{\gamma}} \tag{5.28}$$

The parameter γ is adjusted so that y_{MSY}/K can be fixed.

Deriso (1980) makes the assumption that fishing takes place in a single pulse at the beginning of each year. This approximation is not, however, appropriate for the hake fishery in the ICSEAF Convention Area, where fishing continues throughout the year, and one of the forms of Schnute's model (Schnute 1985) must therefore be used. The total survival rate, τ_i, equals $\exp[-(M+F_i)]$, where F_i must satisfy the VPA equation:

$$\frac{C_i}{B_i} = \frac{F_i}{F_i + M_i} [1 - e^{-(F_i+M)}] \tag{5.29}$$

where C_i is the total catch by mass, i.e. $\sum_{a=k}^{\infty} C_{a,i}\, w_{a+1/2}$

B_i is the biomass at the beginning of year i, y_i, "projected" to time (i+1/2) by increasing the mass of each fish while ignoring mortality effects, i.e.

$$\sum_{a=k}^{\infty} N_{a,i}\, w_{a+1/2}$$

F_i is the instantaneous fishing mortality rate in year i and

M is the rate of natural mortality rate.

The above equation assumes that the rates of fishing and natural mortality are independent of age (after age at recruitment k). The parameters M, k and ρ can be estimated from the auxiliary information. In all subsequent calculations M is taken to be 0.3 [as in the Butterworth (1988a) age-structured operating model], k to be 3 [corresponding to the age at 50% recruitment in Butterworth (*op. cit.*)] and ρ to be 1 (see above).

5.10 The Continuous Schaefer model (Schaefer 1954, 1957, Uhler 1979)

The continuous surplus production function with a linear harvesting term can be written :

$$\frac{dy(t)}{dt} = ry(t)[1 - \frac{y(t)}{K}] - qEy(t) \tag{5.30}$$

Multiplying equation (5.30) by dt/y(t) gives :

$$\frac{dy(t)}{y(t)} = [r - \frac{r}{K}y(t) - qEy]dt \tag{5.31}$$

and integrating equation (5.31) over year i produces :

$$\ell n(y_{i+1}) - \ell n(y_i) = r - r\bar{y}_i/K - q\bar{E}_i \tag{5.32}$$

where $\bar{y}_i$ is the average exploitable biomass in year i. Making the substitution corresponding to the process error assumption then gives :

$$\ell n[(C/E)_{i+1}/(C/E)_i] = r - r\overline{(C/E)_i}/(qK) - q\bar{E}_i$$

The parameters of (5.32) can now be estimated using multi-linear regression, after replacing $\overline{(C/E)_i}$ and $\bar{E}_i$ by their appropriate mean values, taken here to be $[(C/E)_{i+1} + (C/E)_i]/2$ and $(E_{i+1} + E_i)/2$ respectively.

5.11 The Discrete Schaefer model (Schaefer 1954, 1957, Hilborn 1979)

The difference form of the Schaefer production function is :

$$y_{i+1} = y_i + ry_i(1 - y_i/K) - C_i \tag{5.33}$$

Dividing equation (5.33) by y_i produces :

$$y_{i+1}/y_i = 1 + r - (r/K)\, y_i - (C_i/y_i)$$

$$= 1 + r - (r/K)\, y_i - qE_i \tag{5.34}$$

and making the process error assumption, $(C/E)_i = qy_i$, then gives :

$$\frac{(C/E)_{i+1}}{(C/E)_i} = 1 + r - (r/qK)(C/E)_i - qE_i \tag{5.35}$$

Estimates of the parameters of equation (5.35) can be obtained using multi-linear regression.

5.12 The Schnute-77 model (Schnute 1977)

The cpue dynamics are modelled by the equation :

$$\widehat{(C/E)}_{i+1} = \frac{qK}{r}\ \ell n\{1 + \exp[(r - qE_i)(C/E)_i]\ \ \times$$

$$\frac{(r - qE_i)\exp(r - qE_{i+1}) - 1}{[(r - qE_{i+1})\exp(r - qE_i) - 1]}\ \exp(r - qE_i - \frac{qK}{r}(C/E)_i)\} \tag{5.36}$$

which is derived by integrating the continuous representation of the resource dynamics equation with the Schaefer form of the surplus production function (Appendix 5.D). This equation assumes that the observation model $[(C/E)_i = qy_i]$ is exact, and it is therefore implicitly a process error estimator. To convert this to an observation error estimator [called Schnute-77(1)], $(C/E)_i$ is replaced by qy_i in equation (5.36). This procedure is at best *ad hoc* because equation (5.36) is initially derived by assuming no observation error. The cpue dynamics for the observation error estimator are modelled by :

$$\widehat{(C/E)}_i = q\left(\frac{y_{i+1} + y_i}{2}\right) \tag{5.37}$$

with quotas determined according to the formula :

$$\hat{Q}_{0.n}(n+1) = \widehat{(C/E)}_n \, \hat{E}_{0.n} \tag{5.38}$$

An estimation procedure [Schnute-77(2)] which is derived by integrating the continuous representation of the stock dynamics equation with the Schaefer form of the surplus production function can be achieved without making the process error assumption (Appendix 5.E). The stock dynamics are thus modelled by :

$$y_{i+1} = \frac{a_i b_i e^{(r - qE_i)}}{1 + b_i e^{(r - qE_i)}} \tag{5.39}$$

where $a_i = (r - qE_i)\frac{K}{r}$ and

$b_i = y_i/(a_i - y_i)$

If the cpue in year i is assumed to be proportional to the average cpue during year i, i.e.

$$\hat{(C/E)}_i = q\int_0^1 y(i+t)dt$$

then integrating (Appendix 5.E) gives :

$$\hat{(C/E)}_i = \frac{qK}{r}\,\ell n\left[\frac{1 + b_i e^{(r - qE_i)}}{1 + b_i}\right] \qquad (5.40)$$

Quotas are estimated using formula (5.38).

5.13 The Shepherd model (Shepherd 1987)

Shepherd (1982, 1987) argues that certain functional forms for the surplus production function (e.g. the Fox or Schaefer models) which become negative so rapidly if the biomass increases beyond K as to imply density dependent natural mortality, are not realistic. He suggests that to avoid this, surplus production functions be split into two components: one which must always be positive, representing the factors of growth of individual fish and reproduction, and one which is always negative, representing the effects of natural mortality. The positive factors are modelled (in this study) by the Beverton-Holt functional form, resulting in a surplus production function of the form:

$$g(y) = \frac{ay}{1 + y/b} - My \qquad (5.38)$$

The fishery is modelled here by the Butterworth-Andrew equations (see above) :

$$y_{i+1} = y_i + g(y_i) - C_i$$

$$\widehat{(C/E)}_i = q\left(\frac{y_{i+1} + y_i}{2}\right) \tag{5.39}$$

The parameters used in the non-linear minimisation search are a' and K, where a' = a/M (M is given) and K is the carrying capacity. In order to estimate the parameter b, it should noted that at y = K, surplus production is zero, i.e. :

$$0 = aK/(1 + K/b) - MK$$

Solving for b gives :

$$b = K/(a/M - 1) = K/(a' - 1)$$

The instantaneous rate of natural mortality, M, is taken to be 0.3 (Butterworth 1988a). In order to estimate the parameters for a process error estimator, y_i is replaced by $(C/E)_i/q$ in equation (5.38) and (5.39) :

$$\widehat{(C/E)}_{i+1} = (C/E)_i \left[\frac{a'}{1 + (a'-1)(C/E)_i/qK} - 1\right] - qC_i$$

APPENDIX 5.A: COOKE'S METHOD OF ESTIMATING q WHEN ℓn(cpue) MINIMISATION IS USED

Assuming that cpue is estimated by $\hat{q}.\hat{y}$, where $\hat{y}$ is some average of the biomass present during the year (but does not depend on q), the sum of squares function to be minimised (SS) is :

$$SS = \sum_i w_i.[\ell n(C/E)_i - \ell n(\widehat{C/E})_i]^2 \tag{5.A.1}$$

$$= \sum_i w_i \, [\ell n(C/E)_i - \ell n(\hat{y}_i) - \ell n(q)]^2$$

where $(C/E)_i$ is the observed cpue in year i,

$(\widehat{C/E})_i$ is the model-predicted cpue in year i and

w_i is the weight assigned to the data point in year i.

The minimum of SS occurs when the derivatives of SS with respect to the parameters are zero. In particular, this must be true for the parameter q. As $\hat{y}_i$ is independent of q, taking the derivative of SS with respect to q gives :

$$\frac{\partial SS}{\partial q} = \sum_i 2w_i.[\ell n(C/E)_i - \ell n(\widehat{C/E})_i][-1/q] = 0 \tag{5.A.2}$$

dividing by q and simplifying gives:

$$\sum_i w_i.[\ell n(C/E)_i - \ell n(q\hat{y}_i)] = 0 \tag{5.A.3}$$

and expanding $\ell n(q\hat{y}_i)$ and solving for q produces :

$$\hat{q} = \exp\{\sum_i w_i.[\ell n(C/E)_i - \ell n\hat{y}_i]/\sum_j w_j\} \tag{5.A.4}$$

Parameter q thus need not be included in the non-linear search, as it is always determined by equation (5.A.4) once values for the other parameters are given.

APPENDIX 5.B. THE COMBINED BROWN METHOD

In order to use this method, two parameters, Υ and $(\widehat{C/E})_{n-5}$ [following the notation of Vasilyev (1988)], are required. Υ is a smoothing factor and $(\widehat{C/E})_{n-5}$ an estimate of the cpue in year (n-5). The algorithm used to estimate $(C/E)_{n+1}$ is :

$a_1(n-5) = (\widehat{C/E})_{n-5}$

$a_2(n-5) = 0$

FOR $i = n-5$ TO n

$e_i = (C/E)_i - (\widehat{C/E})_i$

$a_2(i+1) = a_2(i) + (1-\Upsilon)^2 e_i$

$a_1(i+1) = a_1(i) + a_2(i) + (1-\Upsilon^2) e_i$

$(\widehat{C/E})_{i+1} = a_1(i+1) + a_2(i+1)$

NEXT i

In general, $(\widehat{C/E})_{i+m}$ (for $m > 0$) can be estimated from the sum of $a_1(i+1)$ and $m[a_2(i+1)]$. In order to estimate the parameters Υ and $(\widehat{C/E})_{n-5}$, the functional :

$$SS = \sum_{i=n-5}^{n} w_i e_i^2 \qquad (5.B.1)$$

must be minimised (see Vasilyev 1988), in which w_i is the weight (equal to 1 in this implementation) assigned to each data point in year i and e_i is the error term in the algorithm above.

APPENDIX 5.C. THE EXPONENTIAL SMOOTHING METHODS

The Exponential Smoothing, Adaptive (Lag 0) and Adaptive (Lag 1) methods require two parameters: Υ (a smoothing factor) and $\widehat{(C/E)}_{n-5}$ [an estimate of cpue in year (n-5)], following the notation of Vasilyev (1988). In addition, the (non-adaptive) Exponential Smoothing method requires an additional smoothing parameter, f. The algorithm used to estimate $(C/E)_{n+1}$ is :

$\tau_1 = 0.2$

$e_b = 0$

$\Sigma = 0$

$r_{mad} = 0.1\ \widehat{(C/E)}_{n-5}$

FOR i = n-5 TO n

  $e_i = \widehat{(C/E)}_i - (C/E)_i$

  $e_b = 0.2e_i + 0.8e_b$

  $\Sigma = \Sigma + e_i$

  $\tau = e_b/r_{mad}$

  IF method = adaptive lag 0 THEN $f = |\tau|$
                                        (Otherwise f input)
  IF method = adaptive lag 1 THEN $f = |\tau_1|$

  $\tau_1 = \tau$

  $\widehat{(C/E)}_{i+1} = \widehat{(C/E)}_i + fe_i + \Upsilon\Sigma$

NEXT i

In order to estimate the parameters Υ and $\widehat{(C/E)}_{n-5}$ [and f for the (non-adaptive) Exponential Smoothing method], the functional :

$$SS = \sum_{i=n-5}^{n} w_i e_i^2 \qquad (5.C.1)$$

must be minimised (see Vasilyev 1988), in which w_i is the weight (equal to 1 in this implementation) assigned to the data point in year i and e_i is the error term in the algorithm above.

APPENDIX 5.D. DERIVATION OF THE SCHNUTE-77 MODEL

This method is based on integration of the continuous form of the Schaefer model under the assumption that cpue is proportional to biomass :

$$\frac{dU}{dt} = rU(1 - \frac{U}{qK}) - qEU \tag{5.D.1}$$

where U is the cpue, q is the constant of proportionality in the cpue-biomass relationship and r and K are the parameters of the Schaefer model. For simplification, the following notation has been used in the derivation of the formula upon which the estimator of equation (5.36) is based :

$$\bar{F}_n = \int_n^{(n+1)} F(t)dt$$

$$a_n = r - q\bar{E}_n$$

$$\beta = r/qK$$

where F is some time-dependent function. It is also assumed that the effort (rate) during year n, $E(n+t)$ $(0 \leq t \leq 1)$ is constant $(\bar{E}_n)$. Dividing equation (5.D.1) by U gives :

$$\frac{1}{U}\frac{dU}{dt} = r - \frac{rU}{qk} - q\bar{E} \tag{5.D.2}$$

$$= a - \beta U$$

Integrating the LHS of equation (5.D.2) over year n [the period $n \leq (n+t) \leq (n+1)$] then gives :

$$\int_{n}^{(n+1)} \frac{1}{U}\frac{dU}{dt}\,dt = \ell n U_{n+1} - \ell n U_{n} = \ell n(U_{n+1}/U_{n}) \tag{5.D.3}$$

Now it can be shown that :

$$\frac{d[\exp(a_n t)/U]}{dt} = \frac{a_n \exp(a_n t)}{U} - \frac{\exp(a_n t)}{U^2}\frac{dU}{dt} \tag{5.D.4}$$

Substituting $(a_n - \beta U)$ for $(1/U)(dU/dt)$ in equation (5.D.4) :

$$d[\exp(a_n t)/U]/dt = \beta \exp(a_n t) \tag{5.D.5}$$

and integrating equation (5.D.5) over year n then gives :

$$\exp(a_n t)/U_{n+1} - 1/U_n = \beta[\exp(a_n t)-1]/\alpha_n \tag{5.D.6}$$

Now integrating equation (5.D.2) over year n gives :

$$\ell n(U_{n+1}/U_n) = a_n - \beta \bar{U}_n \tag{5.D.7}$$

i.e.

$$U_{n+1} = U_n \exp(a_n - \beta \bar{U}_n) \tag{5.D.8}$$

Substituting (5.D.8) for U_{n+1} in equation (5.D.6) and simplifying then gives :

$$\bar{U}_n = a_n [\exp(\beta \bar{U}_n) - 1]/[\beta (\exp(a_n) - 1)] \tag{5.D.9}$$

In order to eliminate all instantaneous quantities, equation (5.D.9) for U_{n+1} is divided by (5.D.9) for U_n :

$$\frac{U_{n+1}}{U_n} = \frac{a_{n+1}}{a_n} \frac{[\exp(\beta.\bar{U}_{n+1}) - 1]/[\exp(a_{n+1}) - 1]}{[\exp(\beta.\bar{U}_n) - 1]/[\exp(a_n) - 1]} \tag{5.D.10}$$

Taking the natural logarithm of both sides of equation (5.D.10) :

$$\ell n(\frac{U_{n+1}}{U_n}) = \ell n\{\frac{a_{n+1}}{a_n} \frac{[\exp(\beta.\bar{U}_{n+1}) - 1]/[\exp(a_{n+1}) - 1]}{[\exp(\beta.\bar{U}_n) - 1]/[\exp(a_n) - 1]}\} \tag{5.D.11}$$

and substituting (5.D.11) into (5.D.7) then gives :

$$a_n - \beta\bar{U}_n = \ell n\{\frac{a_{n+1}}{a_n} \frac{[\exp(\beta.\bar{U}_{n+1}) - 1]/[\exp(a_{n+1}) - 1]}{[\exp(\beta.\bar{U}_n) - 1]/[\exp(a_n) - 1]}\} \tag{5.D.12}$$

Solving for $\bar{U}_{n+1}$ gives equation (5.36).

APPENDIX 5.E. DERIVATION OF THE SCHNUTE-77(2) MODEL

This method is based on integration of the continuous form of the Schaefer model :

$$\frac{dy}{dt} = ry(1 - \frac{y}{K}) - qEy \qquad (5.E.1)$$

$$= (r - qE).y.[1 - \frac{ry}{(r - qE)K}] \qquad (5.E.2)$$

Collecting all terms involving y to the LHS and multiplying by dt gives:

$$\frac{dy}{y[1 - ry/\{(r - qE)K\}]} = (r - qE)dt \qquad (5.E.3)$$

Dividing the LHS of equation (5.E.3) into partial fractions and then integrating both sides gives :

$$\ell n(y) - \ell n[(r - qE)(K/r) - y] = (r - qE)t + F$$

where F is the constant of integration. Collecting terms on the LHS and exponentiating gives :

$$\frac{y}{(r - qE)(K/r) - y} = Fe^{(r - qE)t} \qquad (5.E.4)$$

Setting t = i and solving for F [note that $y(i) = y_i$] produces the result :

$$\frac{y_{i+t}}{(r - qE_i)(K/r) - y_{i+t}} = e^{(r - qE_i)t} \frac{y_i}{(r - qE_i)(K/r) - y_i} \qquad (5.E.5)$$

By making the substitutions :

$$a_i = (r - qE_i)\frac{K}{r} \quad \text{and}$$

$$b_i = y_i/(a_i - y_i)$$

and solving for y, the result :

$$y_{i+t} = \frac{a_i b_i e^{(r - qE_i)t}}{1 + b_i e^{(r - qE_i)t}} \tag{5.E.6}$$

is produced. Setting t = 1 in equation (5.E.6) yields equation (5.39).

In order to show that evaluating $\int_0^1 y(i+t)dt$ leads to equation (5.40), y(i+t) is replaced by equation (5.E.6) to give :

$$\int_0^1 y(i+t)dt \quad \int_0^1 \frac{a_i b_i e^{(r - qE_i)t}}{1 + b_i e^{(r - qE_i)t}} dt \tag{5.E.7}$$

Integrating y(i+t), the RHS of equation (5.E.7) gives :

$$\frac{a_i}{(r - qE_i)}\left[\ell n(1 + b_i e^{(r - qE_i)t}\right]_0^1$$

and simplifying produces equation (5.40).

6 METHODS FOR ESTIMATION OF PRECISION

6.1 Introduction

In order to assess the "quality" of an estimate of a variable or parameter, some estimate of its precision, such as the variance or standard error (s.e.) should be obtained. Another measure of precision is the coefficient of variation (c.v.), which is defined as the ratio of the standard error to the mean. The c.v. provides an immediate indication of the usefulness of an estimate; for example, as a rough guide, if the c.v. is larger than 0.5, the estimate is not statistically different from zero.

The variance estimation procedures considered here depend on the assumption that the $(C/E)_i$ values are independent and identically distributed about their expected values, according to some unknown distribution F. The assumption of independence is unlikely to hold, however, as (*inter alia*) each $\widehat{(C/E)}_i$ depends on the previous year's quota, $C_{(i-1)}$ (for as far back in time as the particular estimation procedure concerned has been used to set quotas, and assuming all the quotas are fully utilised), which in turn depends on $E_{(i-1)}$. Some degree of serial correlation can therefore be expected in the cpue time series for the hake stocks in the ICSEAF Convention Area (Butterworth 1988a).

Now, let $\hat{F}$ be the empirical probability distribution of the observed C_i and $(C/E)_i$, such that :

$$\{\hat{F} : \text{mass } \frac{1}{n}\} \text{ at } x_1, x_2, x_3, .. , x_n \tag{6.1}$$

where each x_i represents an observed $\{C_i, (C/E)_i\}$ data pair.

[The use of the x_i's by a model estimation procedure should be independent of their order, i.e. a statistic $\theta(X_1, X_2, X_3, .. ,X_n)$ should be invariant under permutations of its arguments. The only estimation procedures which satisfy this requirement, however, are those based on the continuous equilibrium assumption; all other procedures utilise the data in an order-dependent manner.]

The "true" variance of an estimated statistic $\hat{\theta}$ (such as $\widehat{MSY}$) is given by :

$$VAR(\hat{\theta}) = E_F[\hat{\theta}(X_1, X_2, X_3, .. ,X_n) - E_F(\hat{\theta})]^2 \tag{6.2}$$

where E_F is the expectation under the true distribution F, and the X_i are the true values of the variables sampled. In order to estimate $VAR(\hat{\theta})$, the methods described below (with the exception of the information matrix method), calculate the value of $\hat{\theta}$ after changing either the set of cpue data points used, or the weights assigned to the data. The estimate of θ obtained from the S'th (artificial) dataset is denoted $\hat{\theta}^S$.

In order to illustrate how the different variance estimation procedures are used in practice, a description of the functional which is minimised in the estimation of the model parameters required for determining $\hat{\theta}^S$ is given for each variance procedure. In general, this functional may be written :

$$SS = \sum_{i=1}^{n} w_i^S \, [\ell n(C/E)_i^S - \ell n(\widehat{C/E})_i^S] \tag{6.3}$$

where $(C/E)_i^S$ is the "observed" cpue for year i and dataset S (certain of the variance estimation procedures require "artificial" sets of "observed" cpue, but in the original model fit the actual observed cpue data are used, in which case the S index is omitted and $w_i = 1$ for all i),

$(\hat{C/E})_i^S$ is the model estimated cpue for year i and dataset S,

n is the number of data points [for certain of the model estimation procedures, the summation in equation (6.3) does not extend over all n data points, but this complication is ignored here for simplicity of presentation] and

w_i^S is a component of a vector of weights (i = 1,..,n), constrained so that $\Sigma w_i^S = n$.

All the variance estimation procedures are conditioned on the historical catch series [i.e. when $(C/E)_i^S$ is generated, it is assumed that $C_i^S = C_i$ and that all the variability is manifest as effort variability].

6.2 The Jack-knife Methods

a) The (basic) jack-knife method

The jack-knife estimate of variance (Tukey 1958) is :

$$\hat{VAR}(\theta) = \frac{n-1}{n} \sum_{j=1}^{n} [\hat{\theta}_{(j)} - \hat{\theta}_{(.)}]^2 \qquad (6.4)$$

where $\hat{\theta}_{(j)}$ is the estimate of θ computed by omitting the j'th data point and assigning a weight of n/(n-1) to the remaining observations and

$\hat{\theta}_{(.)}$ is the average of all the $\hat{\theta}_{(j)}$'s.

In order to estimate $\hat{\theta}_{(j)}$, the functional (6.3) is minimised by adjusting the vector $\underset{\sim}{w}^{S}$ as follows:

$$\begin{aligned} w_i^j &= 0 \qquad (i = j) \\ w_i^j &= \frac{n}{n-1} \qquad (i \neq j) \end{aligned} \tag{6.5}$$

b) The infinitesimal jack-knife method

This method [defined by Jaeckel (1972)], which is equivalent to the Delta method (Efron 1982), computes a standard error for $\hat{\theta}$ by adjusting the weights for each data point x_i. The variance is estimated by:

$$\mathrm{VAR}(\hat{\theta}) = \frac{1}{n^2} \sum_{j=1}^{n} u_{(j)}^2 \tag{6.6}$$

where $$u_{(j)} = \lim_{\varepsilon \to 0} \frac{\hat{\theta}[\underset{\sim}{w}^0 + \varepsilon(\underset{\sim}{\delta}(j) - \underset{\sim}{w}^0)] - \hat{\theta}(\underset{\sim}{w}^0)}{\varepsilon} \tag{6.7}$$

$\underset{\sim}{w}^0$ is the vector of weights for the original data points (1,1,1, ... ,1) and

$\underset{\sim}{\delta}(j)$ is a vector such that :

$$\begin{aligned} \delta(j)_i &= n \qquad (i = j) \\ \delta(j)_i &= 0 \qquad (\text{otherwise}). \end{aligned} \tag{6.8}$$

To calculate $u_{(j)}$, an estimate of $\theta[\underset{\sim}{w}^0 + \varepsilon(\underset{\sim}{\delta}(j) - \underset{\sim}{w}^0)]$ is made by minimising the functional (6.3), where the components of vector $\underset{\sim}{w}^j$ have the values :

$$w_i^j = 1 + \varepsilon\,(n-1) \quad (i = j)$$
$$w_i^j = 1 - \varepsilon \quad (i \neq j) \tag{6.9}$$

and a finite value of $\varepsilon \ll 1$ (in this case $\varepsilon = 0.001$) is used for the computations.

6.4 The (Unconditioned) Bootstrap methods

These methods, developed by Efron (1981 and 1982), assume that the "true" distribution F is identical to the empirical distribution $\hat{F}$. Two Two variations based on this assumption are described below.

a) The "Naive" Bootstrap

This procedure is the fundamental bootstrap procedure defined by Efron (1981), and is the basis for all variations on the method. A large number (S_{max}, where $S = 1,\ldots,S_{max}$ and $S_{max} = 250$ for this study) of random bootstrap samples $x_1^S, x_2^S, x_3^S, \ldots, x_n^S$ is drawn with replacement from $\hat{F}$ and an estimate :

$$\hat{\theta}^S = \hat{\theta}(x_1^S, x_2^S, x_3^S, \ldots, x_n^S) \tag{6.10}$$

is computed from each. The bootstrap estimate of the variance of $\hat{\theta}$ is defined as :

$$\widehat{VAR}(\theta)_{boot} = \frac{1}{S_{max} - 1} \sum_{S=1}^{S_{max}} [\hat{\theta}^S - \theta_{(.)}]^2 \tag{6.11}$$

where $\hat{\theta}^S$ is the estimate of θ from the S'th bootstrap sample and

$\theta_{(.)}$ is the mean of the $\hat{\theta}^S$'s.

In order to estimate $\hat{\theta}^S$ for the "naive" bootstrap, the functional (6.3) is minimised, with the vector $\underline{w}^S$ being defined by equating each w_i^S to the number of times the value i is selected during sampling n times with replacement from the set {1,2,3,...,n}. Thus for each S :

$$\sum_{i=1}^{n} w_i^S = n \tag{6.12}$$

where each w_i^S is a positive integer, or zero.

According to Efron (1982), $\hat{F}$ is the non-parametric maximum likelihood estimate (MLE) of F and $\widehat{VAR}(\theta)_{boot}$ is the non-parametric MLE of $\widehat{VAR}(\theta)$. The limit as S_{max} tends to infinity of $\widehat{VAR}(\theta)_{boot}$ is $VAR(\hat{\theta})$ (Efron 1977). This variance estimation procedure is called "naive" as it does not reflect the regression nature of the problem under consideration (with data for different years having different degrees of influence on the estimate under consideration), and some of the artificial data sets may be unrepresentative (a bootstrap sample will generally not include effort data for a number of years in the available series, so that problems may arise when, for example, the selected set contains very few points near the start or near the finish of the shortish series). A variance estimation procedure that does not take the regression nature of the problem into account will be called "unconditioned".

b) The "naive permuted" Bootstrap

This method, defined by Davidson *et al.* (1986) is a procedure designed to reduce the sampling error due to the use of Monte-Carlo techniques in implementing the "naive" bootstrap procedure described above. The method is identical to the "naive" bootstrap, except that the random samples are chosen so that each x_i is selected the same number of times in the S_{max} artificial data sets. This technique is claimed by the authors to require fewer Monte-Carlo trials than the "naive" bootstrap method, to obtain equally precise variance estimates.

For the "naive permuted" bootstrap, the w_i^S are selected as in the "naive" bootstrap, although subject to the further constraint that the sums over all bootstrap simulations of w_i^S equal the number of bootstrap simulations, i.e.

$$\sum_{S=1}^{S_{max}} w_i^S = S_{max} \quad \text{for each } i = 1 \ldots n \tag{6.13}$$

6.4 *Ad hoc* Bootstrap methods

d) The Punt no. 1 Bootstrap

This method is an entirely *ad hoc* procedure which has been designed so that the weight assigned to each data point is non-zero. The purpose of this is to remove one of the defects of the "naive" bootstrap, namely that in any one bootstrap sample, many of the most influential data points determining sustainable yield/current biomass may be omitted (i.e. lack of conditioning referred to in the previous section), resulting in unrepresentative parameter and variable estimates.

The bootstrap estimates, $\hat{\theta}^S$, are calculated as follows :

The n weights w_i^S are selected from the uniform distribution U[1,10] and normalised so that $\sum_i w_i^S = n$. Then $\hat{\theta}^S$ is estimated by minimising the functional (6.3).

e) The Punt no.2 Bootstrap

This method (again *ad hoc*) is designed, like the Punt no.1 bootstrap, so that no data point has a non-zero weight. It furthermore ensures that the minimum weight is 0.5. The method is similar to the Punt no.1 bootstrap, except that the w_i^S are normalised so that $\Sigma w_i^S = n/2$. The value 0.5 is then added to each weight w_i^S and the functional (6.3) is minimised to obtain an estimate of $\hat{\theta}^S$.

f) The Butterworth-Punt Bootstrap

This further *ad hoc* bootstrap procedure attempts to take account of the fact that the variable estimates tend to be more sensitive to (influenced by) some of the data points than others. The method first computes the sensitivity of, say, $\hat{Q}_{0.1}$ to a 1% change in $(C/E)_i$:

$$S_i = \left| \frac{\hat{Q}^{+1}_{0.1}(i) - \hat{Q}_{0.1}}{\hat{Q}_{0.1}} \right| + \left| \frac{\hat{Q}^{-1}_{0.1}(i) - \hat{Q}_{0.1}}{\hat{Q}_{0.1}} \right| \qquad (6.14)$$

where $\hat{Q}_{0.1}$ is the estimate of $Q_{0.1}$ using the original data series,

$\hat{Q}^{+1}_{0.1}(i)$ is the estimate of $Q_{0.1}$ after adjusting (only) $(C/E)_i$ to $1.01(C/E)_i$ and

$\hat{Q}^{-1}_{0.1}(i)$ is the estimate of $Q_{0.1}$ after adjusting (only) $(C/E)_i$ to $0.99(C/E)_i$.

In order to estimate $\hat{\theta}^S$, the weights w_i^S are selected from the uniform distribution $U[S_i, 10S_i]$ and normalised so that their sum is n. Then $\hat{\theta}^S$ is estimated by minimising the functional (6.3).

6.5 The (Conditioned) bootstrap methods

These methods follow the "naive" bootstrap, except that the bootstrap samples are generated taking into account the regression nature of the estimation. In both of these techniques, the variance estimation procedure assumes that the noise is pure observation error.

a) The Residual ("Conditioned") Nonparametric Bootstrap

This method (Efron 1982) is designed to estimate the variance of parameters in general regression situations. Suppose a general regression model is :

$$(C/E)_i = [C/E(\hat{\beta})]_i + \varepsilon_i \qquad (i = 1, 2, .. ,n) \tag{6.15}$$

where $(C/E)_i$ is the observed cpue in year i,

$\widehat{(C/E)}_i$ is the model-predicted cpue for year i,

β is a vector of model parameter estimates and

ε_i is the error term drawn from distribution G.

In order to estimate the parameters β, the functional (6.3) must be minimised. As the distribution G is unknown, its MLE, $\hat{G}$, is used :

$$\{ \hat{G} : \text{mass } \frac{1}{n} \} \text{ at } \varepsilon_1, \varepsilon_2, \varepsilon_3, .. ,\varepsilon_n \tag{6.16}$$

For the bootstrap samples, ε_i^S is selected with replacement from $\hat{G}$, and $(C/E)_i^S$ thus equated to $[C/E(\hat{\beta})]_i + \varepsilon_i^S$. Some function, $\hat{\theta}^S$, of the estimated parameters $\hat{\beta}^S$ is then calculated. VAR($\hat{\theta}$) is defined as the variance of the $\hat{\theta}^S$'s [according to formula (6.11)]. Sometimes the errors ε_i are bias-corrected by a factor n/(n-p) where p is the number of model parameters estimated, based upon analogy to linear models. This correction has not been implemented here, however, and the s.e. and c.v. estimates could consequently be negatively biased. (For a 3-parameter model and the 21 years of cpue data considered here, the negative bias contribution to standard error estimates would be about 8%, if this factor operates linearly.)

b) The ("Conditioned") Parametric Bootstrap (Efron 1982, 1985)

This variance estimation procedure follows the spirit of the residual bootstrap procedure except that the random sample is generated using a parametric distribution. In this case the log-normal distribution has been assumed, because this assumption is consistent with the fact that the operating model cpue is log normally distributed, and also because it guarantees that the artificial cpue values generated (by the variance estimation procedure) are always positive. The bootstrap sample consists of values x_i^S such that:

$$x_i^S = x_i e^{\varepsilon_i} \qquad \varepsilon_i \sim N(0;\sigma^2) \tag{6.17}$$

where σ^2 is estimated from the residuals (η_i) of the model fit to the data, with a bias correction factor assumed by analogy with linear models :

$$\hat{\sigma}^2 = \frac{1}{n - p} \Sigma \eta_i^2 \qquad (6.18)$$

(where n and the residuals in the summation may alter if the model estimation procedure uses less than the full data series to estimate the model parameters).

When computing the estimates $\hat{\theta}^S$, the functional (6.3) is minimised, adjusting the model-estimated cpue as indicated by equation (6.17), i.e.

$$(C/E)_i^S = (\hat{C/E})_i \, e^{\varepsilon_i} \qquad \varepsilon_i \sim N(0;\hat{\sigma}^2) \qquad (6.19)$$

with $w_i^S = 1$. Standard errors are computed using the usual bootstrap formula (6.11).

6.6 The Information Matrix Method

The true asymptotic variance-covariance matrix for the parameters of a model is the inverse of the information matrix, which is simply:

$$I_{jk} = \frac{1}{\sigma^2} \sum_{i=1}^{n} \frac{\partial f_i(\underset{\sim}{X},\underset{\sim}{\beta})}{\partial \beta_j} \frac{\partial f_i(\underset{\sim}{X},\underset{\sim}{\beta})}{\partial \beta_k} \qquad (6.20)$$

where $\underset{\sim}{\beta}$ is the vector of model parameters,

X_i is the i'th data point and

$f_i(\underset{\sim}{X},\underset{\sim}{\beta})$ is the model under consideration.

The variance of a variable $Y = Y(\underset{\sim}{\beta})$ is approximated by :

$$\widehat{VAR}(Y) = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{\partial Y}{\partial \beta_i} \frac{\partial Y}{\partial \beta_j} COV(\beta_i, \beta_j) \tag{6.21}$$

In relation to the functional (6.3), the model in this case is :

$$\begin{aligned} f_i(\underline{X}, \underline{\beta}) &= \widehat{(C/E)}_i \\ &= g_i[\{(C_j, E_j) : j = 1 \, .. \, n\}, \underline{\beta}] \end{aligned} \tag{6.22}$$

where, for the Butterworth-Andrew model, for example, $\underline{\beta} = (r, q, MSY)$.

6.7 Confidence intervals

In order to estimate 95% confidence intervals for estimates of a parameter $\hat{\theta}$, three methods can be used.

a) Standard intervals

This method sets a 95% confidence interval for $\hat{\theta}$ by :

$$(\hat{\theta} - 1.96\,\hat{\sigma}\;,\; \hat{\theta} + 1.96\,\hat{\sigma}) \tag{6.23}$$

where $\hat{\theta}$ is the estimate of the quantity θ and
$\hat{\sigma}$ is an estimate of the standard error of $\hat{\theta}$.

Confidence intervals estimated in this way are symmetrical and require only an estimate of σ [for which, according to Efron (1987), only 100 bootstrap simulations are needed]. This method has been shown by Efron (*op. cit.*) to provide badly biased intervals in some situations, however. It is used here in combination with the jack-knife variance estimation methods.

b) The percentile method

The percentile method described by Efron (1981) and Buckland (1984) produces direct estimates of confidence intervals for the parameter estimates obtained. The estimate of the confidence interval is computed from the set of bootstrap estimates after sorting them into ascending order. If N Monte-Carlo trials are performed, the 95% confidence interval for $\hat{\theta}$ is then estimated to be $[\hat{\theta}^{S}_{0.025N}, \hat{\theta}^{S}_{0.975N}]$, with $\hat{\theta}^{S}_{0.025N}$ and $\hat{\theta}^{S}_{0.975N}$ obtained by linear interpolation within the ordered set. This technique has been used to calculate the variance and confidence interval estimates reported by Butterworth and Andrew (1984) and Butterworth and Andrew (1987b), and indicates that some estimates have skew distributions (see, for example, confidence interval estimates for MSY given in Figure 10 of the latter reference). Efron (1987) states that to use this method accurately requires at least 1000 bootstrap simulations. Buckland (1984) gives more rigorous formulae for the confidence intervals in terms of N, but the simple formulae above have been used here for simplicity and are sufficiently accurate for the purposes of this work.

c) The Bias-Corrected (BC) Percentile method

The bias corrected percentile method (Efron 1982, Buckland 1984) is a variation arising from the observation that the median of the $\hat{\theta}^{S}$'s is not necessarily equal to the original estimate $\hat{\theta}$. This method provides an adjustment to the interval to account for this lack of symmetry. The confidence interval predicted by the bias-corrected percentile method is then :

$$[\widehat{CDF}^{-1}(\phi(2z_0-z_\alpha)),\ \widehat{CDF}^{-1}(\phi(2z_0+z_\alpha))] \tag{6.24}$$

where

CDF(t) is the probability $\{\theta \le t\}$,

ϕ is the cumulative distribution function for a standard normal random variate,

z_0 is the cumulative probability that the mean of the $\hat{\theta}^S$'s is less than or equal to $\hat{\theta}$ and

z_α is the 2α percentage point for the standard normal distribution.

7 THE MODEL SELECTION METHOD

7.1 Estimating bias and expected discrepancy for the model estimation procedures

The model selection process proposed by Linhart and Zucchini (1986), based on the minimum estimated expected discrepancy of a variable or parameter estimate, is used to assess how accurately and precisely the various proposed production model estimation procedures are able to estimate the management variables and parameters E_{MSY}, MSY, Q_{MSY}, $E_{0.1}$ and particularly $Q_{0.1}$. [A variable is any quantity which changes with time (e.g. Q_{MSY} and $Q_{0.1}$).]

The relative bias of model estimation procedure M in estimating a management variable A, $B^M(A)$, is defined as :

$$B^M(A) = E\{ [\hat{A}^M - A^{true}]/A^{true} \} \tag{7.1}$$

where A^{true} is the true value of A for the stock,

$\hat{A}^M$ is the estimate of A provided by estimation procedure M and

E indicates the expectation.

The discrepancy of model estimation procedure M in estimating a management variable A, $\Delta^M(A)$, is defined here as :

$$\Delta^M(A) = \left|\hat{A}^M - A^{true}\right|/A^{true} \tag{7.2}$$

[Although use of the root mean square error is more common when defining expected discrepancy, the above definition is used here following the suggestion of Butterworth (1988a).]

As the true values of the management variables cannot be known exactly, a generalised operating model [defined by Linhart and Zucchini (1986) as "the nearest representation of the 'true situation' which it is possible to construct by means of a probability model"] is used to provide the "true" values of the variables and parameters. A number R_{max} (reasonable computer time restrictions here dictated a value for R_{max} of 250) of sets of artificial cpue data are produced, based on the error structure of the operating model. The model estimation procedures under consideration are then used in turn to calculate estimates of the management variables from each of the artificial data sets. For the variable $Q_{0.1}(n+1)$, for example, the quantity estimated by procedure M using artificial data set R is denoted by $\hat{Q}^{M}_{0.1,R}(n+1)$. Each estimate of $Q_{0.1}(n+1)$ is then compared with the "true" value, and values of the deviation and discrepancy with respect to data set R, $[B^M_R(A)$ and $\Delta^M_R(A)$ respectively$]$ are computed:

$$B^M_R(A) = [\hat{A}^M_R - A^{\text{"true"}}_R]/A^{\text{"true"}}_R \tag{7.3}$$

and

$$\Delta^M_R(A) = \left|\hat{A}^M_R - A^{\text{"true"}}_R\right|/A^{\text{"true"}}_R \tag{7.4}$$

Estimates of relative bias $B^M(A)$ and expected discrepancy $E\{\Delta^M(A)\}$ can then be obtained by finding the average value (which then corresponds to the estimated expected value) of $\{B^M_R(A) : R = 1 .. R_{max}\}$ and $\{\Delta^M_R(A) : R = 1 .. R_{max}\}$ respectively. Note that when $A^{\text{"true"}}_R$ is constant across the simulations [when equal to $E^{\text{"true"}}_{0.1}$, for example; in contrast, $Q^{\text{"true"}}_{0.1}$ depends on the particular sequence of noise $\{\varepsilon_y\}$ in the stock-recruit relationship, which may differ between artificial data sets (see Appendix 7.A)]:

$$\hat{B}^{M}(A) = \left[\frac{1}{R_{max}} \sum_{R=1}^{R_{max}} \hat{A}_R^{M} - A^{\text{"true"}} \right] / A^{\text{"true"}} \tag{7.5}$$

The estimated bias and expected discrepancy in the case when $A_R^{\text{"true"}}$ is not constant over all simulations will not necessarily be unbiased estimators of the true bias and expected discrepancy, but this complication is ignored for the purposes of this study.

The discrepancy between the operating model and an estimate produced by the selected approximating model is made up of the "error due to approximation" and the "error due to estimation". [An approximating model in this context is a member of the approximating family of models (i.e. equation (3.1) or (3.10) with specific functional forms chosen for G(.) and H(.)) with a set of specific values assigned to the model parameters.] In order to illustrate these two types of "error", the example of approximating a continuous curve by a histogram is used. Figure 7.1(a) shows the curve which is to be approximated (the "true" situation or "operating model"). If the discrepancy is measured by the absolute difference in area between the histogram and the operating model, Figure 7.1(b) illustrates the best (smallest discrepancy) fit to the operating model which can be obtained by a histogram with the specified class width. Figure 7.1(c) represents an estimate of (b) obtained when a finite-sized data set is used for the estimation. The "error due to approximation" in this case is the difference between curves (a) and (b) and the "error due to estimation" the difference

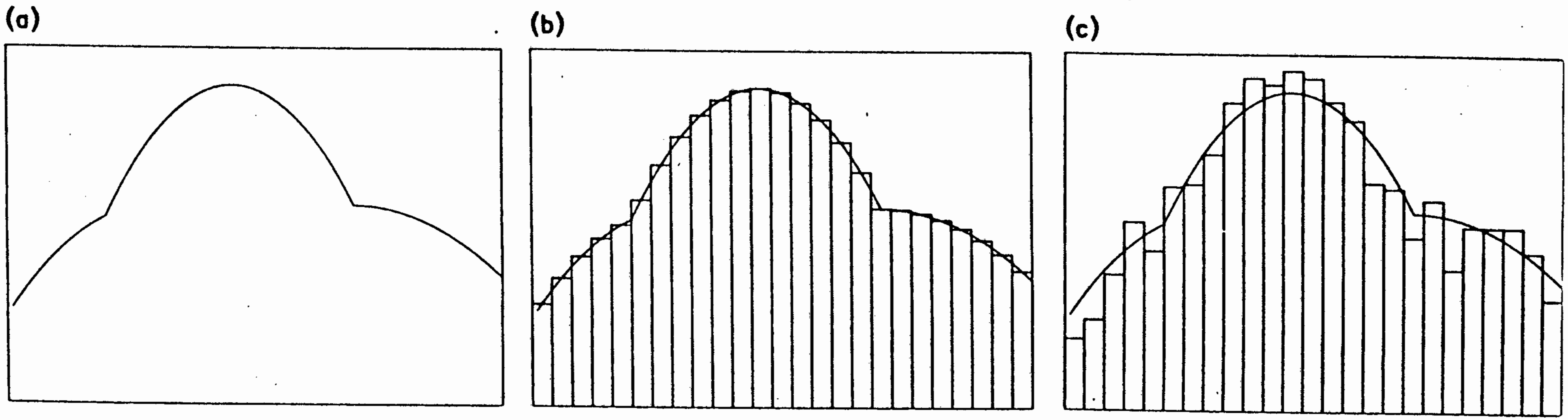


Figure 7.1: (a) the continuous curve which is to be approximated. (b) the histogram which provides the smallest discrepancy and (c) a histogram which estimates the histogram in (b) when the data sample used in the estimation is finite sized.

between curves (b) and (c). The estimated total discrepancy is a representation of the "sum" of these two errors.

7.2 Estimating bias and expected discrepancy for the variance estimation procedures

The estimation of the bias and expected discrepancy of the different variance estimation procedures is analogous to the estimation of these quantities when assessing the performance of the model estimation procedures. For the case when $A_R^{\text{"true"}}$ is constant across the simulations, the "true" value of the variance of an estimate of a variable (or parameter) A, $VAR(\hat{A})$, is computed directly from the set $\{\hat{A}_R^M : R = 1 \text{ to } R_{max}\}$ according to the formula :

$$VAR(\hat{A}^M) = \frac{1}{R_{max}-1} \sum_{R=1}^{R_{max}} (\hat{A}_R^M - \bar{\hat{A}}^M)^2 \tag{7.6}$$

$$\text{where} \quad \bar{\hat{A}}^M = \frac{1}{R_{max}} \sum_{R=1}^{R_{max}} \hat{A}_R^M$$

When $A_R^{\text{"true"}}$ is not constant across the simulation data sets (e.g. $Q_{0.1}$ for operating models with process error terms), each $\hat{A}_R^M$ has a different "true" variance, $VAR(\hat{A}_R^M)^T$, which is estimated by the following procedure:

(i) The parameters $\hat{a}$, $\hat{b}$ and $\hat{\sigma}^2$, i.e. the estimates of the intercept, slope and residual variance, respectively, for the linear regression of $\hat{A}_R^M$ against $A_R^{\text{"true"}}$ (where $A_R^{\text{"true"}}$ is the independent variable and $\hat{A}_R^M$ the dependent variable), are computed

(ii) The "true" variance of $\hat{A}_R^M$ is then estimated analogously to the estimation, for a linear model, of the variance of a single point (Johnson 1972) :

$$\mathrm{VAR}(\hat{A}_R^M)^T = \hat{\sigma}^2 \left[1 + \frac{1}{R_{max}} + (A_R^{\text{"true"}} - A^{\text{"true"}})^2 / SS_2 \right] \qquad (7.7)$$

where $SS_2 = \sum_{R=1}^{R_{max}} (A_R^{\text{"true"}} - A^{\text{"true"}})^2$

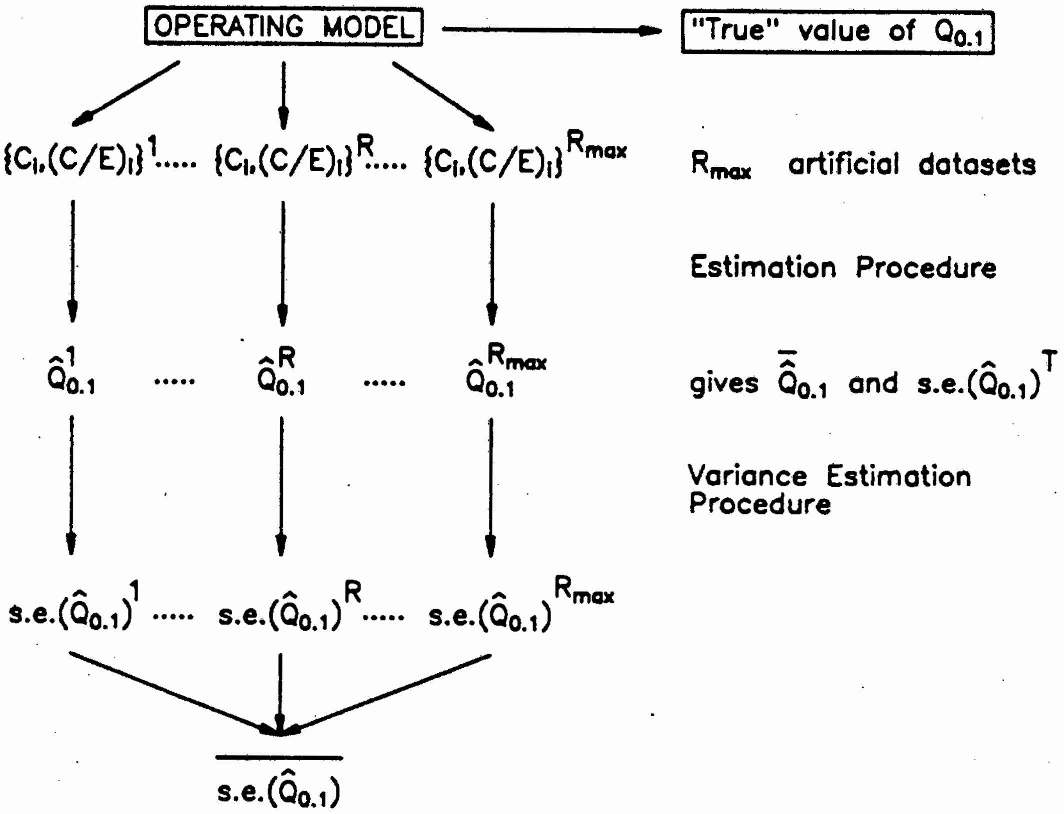
$$A^{\text{"true"}} = \frac{1}{R_{max}} \sum_{R=1}^{R_{max}} A_R^{\text{"true"}}$$

Again, some bias in the estimated bias and expected discrepancy of the variance of an estimate of management variable A may be anticipated when $A_R^{\text{"true"}}$ is not constant across the simulations.

The complete process of estimating biases for both model estimation procedures and variance estimation procedures is illustrated diagrammatically in Figure 7.2.

7.3 Specification of the operating models

At present there exists no generally accepted age-structured operating model, in the sense of Linhart and Zucchini (1986), which represents the "true" underlying situation in the fishery considered. Thus the age-structured model proposed by Butterworth (1988a) [henceforth referred to as the Butterworth age-structured operating model (Appendix 7.A)] is used here as the operating model, although in the preliminary stages of this study three of the model estimation procedures currently used by ICSEAF for management of the resource [the Babayan *et al.* (Fox



Bias of $Q_{0.1}$ estimation procedure $= \bar{\hat{Q}}_{0.1} - \hat{Q}_{0.1}^{\text{"true"}}$

Bias of s.e. estimator $= \overline{s.e.(\hat{Q}_{0.1})} - s.e.(\hat{Q}_{0.1})^T$

Figure 7.2: Flowchart of the method used to estimate the biases of model estimates and of variance estimates which are reported in this thesis.

form) Linear Method (with unsmoothed cpue data) procedure (Bn-F-GLU), the Butterworth-Andrew y_1 = K (Fox form) observation error estimator (BA-F-OK) and the Lleonart *et al.* (q estimated) (Fox form) (with unsmoothed cpue data) process error estimator (Ll-F-PEU)] were also used as operating models (see Appendix 7.B). [In these preliminary stages, the "true" parameters and variables of the three operating models were obtained by fitting the historical hake catch-effort data for ICSEAF Divisions 1.3 + 1.4 from 1965 to 1985 (see Table 7.1(b) for annual catches and Table 7.2 for annual effort values) to these models, using their associated model estimation procedures.] The Butterworth age-structured operating model corresponds closely to the stock in this Division, its parameter values having been chosen using the results of VPA and by fitting the BA-F-OK procedure to the actual cpue data (Butterworth 1988a).

In the case of the three operating models used by ICSEAF, all error in the artificially generated cpue data sets is assumed to be observational, i.e. the error distribution of $(C/E)_i$ is:

$$(C/E)_i^{\text{Artificial}} = (C/E)_i^{\text{Actual}}\, e^{\varepsilon_i} \qquad \varepsilon_i \sim N(0;\hat{\sigma}^2) \qquad (7.8)$$

where $(C/E)_i^{\text{Actual}}$ is NOT the observed historical cpue value but instead is equal to $\widehat{(C/E)}_i$, estimated for the year concerned by fitting the observed data using the estimation procedure corresponding to the operating model being considered. The value of $\hat{\sigma}$ is the estimate of the standard deviation of the ℓn(cpue) residuals for this fit. It should be noted that for the Butterworth-Andrew observation error estimator, which assumes :

$$\hat{(C/E)}_i = q\left(\frac{y_i + y_{i+1}}{2}\right) \qquad (7.9)$$

this error distribution corresponds to log-normal catchability (q) fluctuation, for which ℓn(cpue) minimisation is appropriate in the fitting procedure (see Chapter 3).

For the Butterworth age-structured operating model, however, the data generation procedure is more complex, as both observation error (measured by σ_q) and process error (measured by σ_r) are involved - this is explained in detail in Appendix 7.A. For all the operating models, the time-series of observed catches remains unaltered in the process of artificial data generation; only the effort time-series changes from one artificial data set to the next.

7.4 Testing the model and variance estimation procedures

In order to determine which of the proposed model estimation procedures provides the best estimates (in the sense, ultimately, of minimum expected discrepancy) of the management variables, an initial screening process is carried out in which the bias for each management variable is estimated using three different combinations of error types (pure observation error: $\sigma_q = 0.13$, $\sigma_r = 0$; mixed error: $\sigma_q = 0.1$, $\sigma_r = 0.2$ and pure process error: $\sigma_q = 0.0$, $\sigma_r = 0.3$), and the model estimation procedures which perform inadequately (i.e. show large biases) are immediately eliminated. To ascertain whether the better results among the procedures which remain are, perhaps, pertinent only to the particular set of parameter values chosen for the operating model, sensitivity tests are performed to test the robustness of these remaining procedures to changes in some of the operating model parameters. Figure 7.3 provides a diagrammatic representation of this exercise. The alternative parameter values used to perform these robustness tests are given in Table 7.3. The final selection of model estimation procedures is made by comparing their estimated expected discrepancies for $Q_{0.1}$, in particular, when different values of the operating model parameters are used.

Similarly, in order to determine which of the proposed variance estimation procedures provide the best estimates of the variance of the management variables (again in the sense of minimum expected discrepancy), an initial screening process is carried out in which the biases of the s.e.'s and c.v.'s of the estimates of $E_{0.1}$ and $Q_{0.1}$ provided by the three model estimation procedures in current use by ICSEAF (Bn-F-GLU, BA-F-OK and L1-F-PEU) are computed. The variance estimation procedures which are consistently the most accurate are selected. The discrepancies of these variance estimation procedures, used in conjunction with three of the best model estimation procedures selected by the methods described in the preceding paragraphs, in their calculation of the s.e.'s and c.v.'s of the estimates of $E_{0.1}$ and $Q_{0.1}$, are then computed. Final selection of variance estimation procedures is made by comparing these discrepancies.

In order to test whether the serial correlation effects described in Chapter 4 are likely to bias the variance and management variable estimates substantially, the testing procedures above are adapted to test the effect of the m years following the initial n years of the data series [during which catches are set to the values given in Table 7.1(b)] in which the same model estimation procedure is used both for

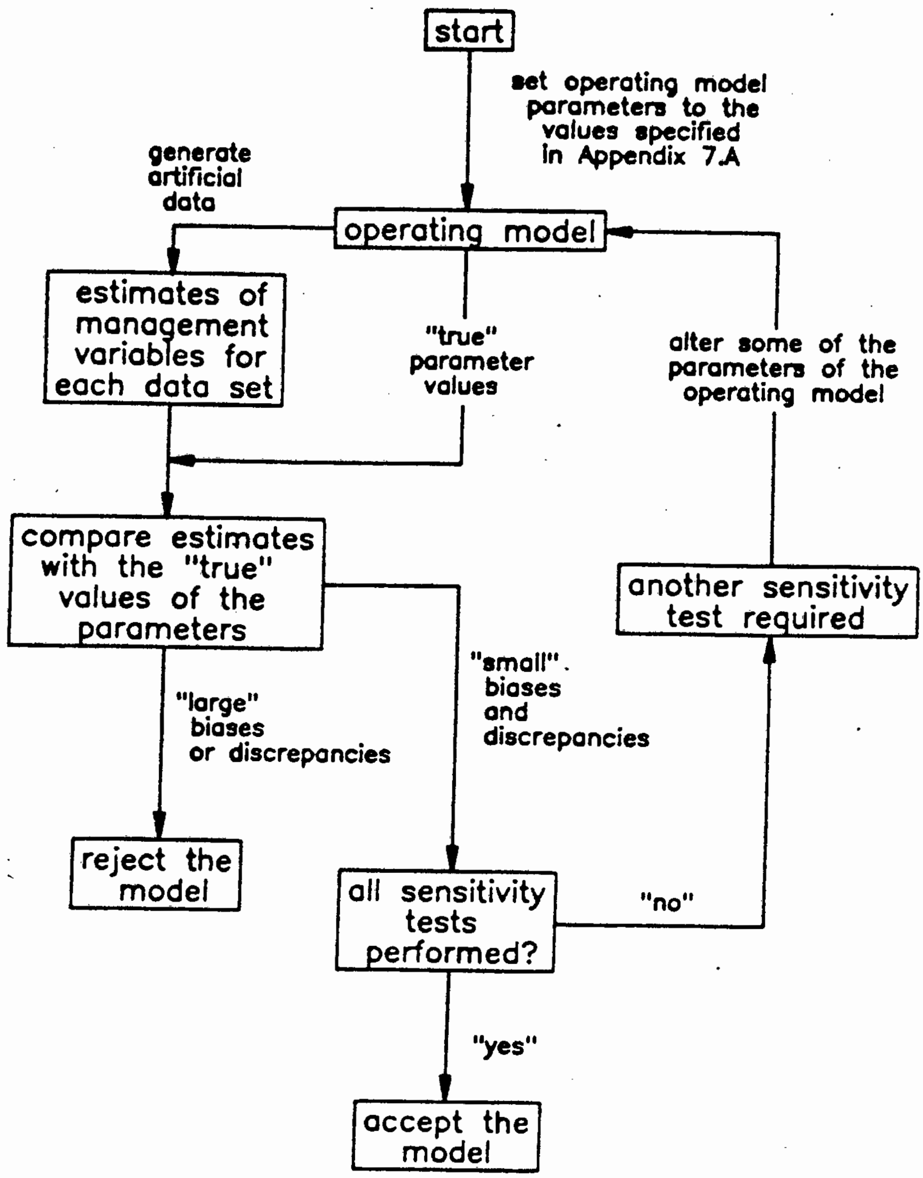


Figure 7.3: Flowchart of the model-selection method used to identify the estimation procedures which perform best in terms first of the accuracy and then of the robustness of the management variable estimates produced. The robustness (sensitivity) tests made are summarised in Table 7.3.

assessing the stock and for setting quotas. During these m years of "serially correlated" data (starting from year 22, or "1986"), the catch represents either the $f_{0.1}$ strategy quota predicted by the particular model estimation procedure considered, or the current exploitable stock size - whichever is the smaller. [Considering the "current status" of the hake resource (given by the operating model), however, it is highly unlikely that, in any one of the simulations, the designated quota will exceed the current biomass (unless the model estimation procedure provides strongly positively biased estimates of quotas)]. The catch-effort series [now (n+m) years long, i.e. comprising data from 1965 to (1985+m)] is then used by the model estimation procedure to estimate the management variables at the end of this period, and these estimates are compared with their "true" values. As the catch series for any simulation trial is a function of the particular errors generated by the operating model during that simulation, even when the operating model error structure is pure observation error, the "true" values of management variables which depend on current biomass ($Q_{0.1}$ and Q_{MSY}) will vary. In contrast, for a management variable which does not depend on the current biomass (MSY, E_{MSY} and $E_{0.1}$), the "true" value remains the same.

All computations reported in this thesis were performed using single precision arithmetic [about six significant figures for the particular computer used (a Sperry Univac 1108)]. This reflects the way in which the 106 model estimation and 10 variance estimation procedures have traditionally been applied in obtaining estimates for presentation to ICSEAF. Because of this, the estimates (especially of variances) which have been calculated may be further biased to some extent by numeric rounding error.

APPENDIX 7.A: SPECIFICATION OF THE AGE-STRUCTURED OPERATING MODEL

The age-structured operating model used in this study is that defined by Butterworth (1988a), except that the time period considered has been extended by one further year (see Table 7.1b). It incorporates density dependent recruitment which is functionally dependent on the spawning biomass, and includes a number of error terms (some of which may not apply in certain of the simulations).

The resource dynamics are described as follows (the symbols used are defined below) :

Basic dynamics:

$$N_{y+1,a+1} = N_{y,a} \exp(-Z_{y,a}) \qquad (7.A.1)$$

where

$Z_{y,a} = M + S_a F_y$

$S_a = \{1 + \exp[-(a-a_r)/\delta]\}^{-1}$

$a = 0,1,....,a_{max}$

$y = 1,2,....,n$

Stock-recruit relationship:

$$N_{y,0} = e^{\epsilon_y} \alpha B^s_y (\alpha\beta + B^s_y)^{-\gamma} \qquad (7.A.2)$$

where

$B^s_y = \sum_{a=a_m}^{a_{max}} w_a N_{y,a}$ and

ϵ_y from $N(0;\sigma_r^2)$

Catch by mass:

$$C_y = \sum_{a=0}^{a_{max}} w_{a+1/2} N_{y,a} S_a F_y [1 - \exp(-Z_{y,a})]/Z_{y,a} \qquad (7.A.3)$$

Effort/fishing-mortality relationship:

$$F_y = e^{\eta_y} qE_y \qquad \text{with } \eta_y \text{ from } N(0;\sigma_q^2) \qquad (7.A.4)$$

Annual average exploitable biomass (taken as mid-year value):

$$B_y^e = \sum_{a=0}^{a_{max}} w_{a+1/2} S_a N_{y,a} \exp[-Z_{y,a}/2] \qquad (7.A.5)$$

Symbols in order of appearance :

$N_{y,a}$ - Number of fish of age a at the start of year y

$N_{y,0}$ - 0-year-class strength ("recruits") in year y

$Z_{y,a}$ - Total mortality on age-class a in year y

M - Natural mortality (assumed independent of age and year)

S_a - Age-specific selectivity ($S_a \to 1$ as $a \to \infty$)

F_y - Asymptotic fishing mortality in year y (i.e. fishing mortality as $a \to \infty$)

a_r - Age at 50% recruitment to the fishery

δ - (Logistic) selectivity function parameter (selectivity becomes knife-edged as $\delta \to 0$)

B_y^s - Spawning biomass at the start of year y

α,β,γ - Parameters of the stock-recruit relation (extended Beverton-Holt form), about which recruitment is in general log-normally distributed

a_m - Age at maturity

w_a - Mass of fish of age a at the start of the year

$w_{a+1/2}$ - Mass of fish of age a in the middle of the year

C_y - Catch (by mass) in year y

q - (Modal) catchability coefficient, about which annual catchability is log-normally distributed

E_y - Fishing effort applied in year y

B_y^e - Average exploitable biomass during year y

$N(0;\sigma^2)$ - Normal distribution with mean zero and standard deviation σ.

The initial conditions correspond to the deterministic unexploited equilibrium level for the stock (i.e. age-structure corresponding to $\varepsilon_y = 0$, $F_y = 0$ for $y < 0$):

$$N_{1,a} = N_{0,0}e^{-aM} \qquad (7.A.6)$$

where

$$N_{0,0} = [(\alpha \sum_{a=a_m}^{a_{max}} w_a e^{-aM})^{1/\gamma} - \alpha\beta][\sum_{a=a_m}^{a_{max}} w_a e^{-aM}]^{-1} \qquad (7.A.7)$$

by substitution from (7.A.2). From (7.A.5), the deterministic pristine exploitable biomass (at mid-year) is given by:

$$K^e = \sum_{a=0}^{a_{max}} w_{a+1/2}\, S_a\, N_{0,0}\, e^{-(a+1/2)M} \qquad (7.A.8)$$

In his specification of the parameter values, Butterworth (1988a) has attempted to simulate a situation typical of the ICSEAF hake stocks. Listed below are the values considered to be reasonably representative of the hake stock in Divisions 1.3 + 1.4 :

M = 0.3 (yr^{-1})

a_{max} = 9 (yr)

a_m = 4 (yr)

a_r = 3 (yr)

δ = 0.5 (yr)

$w_{a+1/2}$ - see Table 7.1(a) (kg)

w_a = $1/2(w_{a+1/2} + w_{a+1/2})$ (kg)

α = 6300 (million)

β = 0.16

γ = 1.0

q = 0.0004 (ESP OTB-7 t/h)$^{-1}$

σ_r = 0.2

σ_q = 0.1

n = 21

C_y - see Table 7.1(b) ('000 tons)

Estimates of the variance of the two noise terms, η_y and ε_y (σ_r^2 and σ_q^2 respectively), are derived as follows. An estimate of σ_r^2 is obtained from a plot of the 0-year class strength against spawning biomass, as derived from VPA. The sum of the two variances (assuming zero co-variance) constitutes the net fluctuation of the observed cpue data about the simple (e.g. production model) trend for ℓn(cpue) residuals :

$$\sigma = \sqrt{\sigma_q^2 + (0.44\ \sigma_r)^2} = 0.13$$

from which an estimate of σ_q can be made (Butterworth 1988a). The value of 0.13 for σ is estimated using the Butterworth-Andrew (Fox form) observation error estimator (BA-F-OK) fit to the data from Divisions

1.3 + 1.4 [Butterworth *et al.* (1986a), Tables 1,3 and AII]. The values listed above provide the following deterministic equilibria [all biomass variables (B^s_y, B^e_y, K^e) have units of '000 tons]:

$K^e = 3000$

$MSY = 251$

$B^e_{MSY}/K^e = 0.39$

which are similar to those produced by the BA-F-OK procedure from data for Divisions 1.3 + 1.4 (Butterworth *et al.* 1986a, Table 1).

The "true" value of $Q_{0.n}(n+1)$ is obtained by determining the fishing mortality $F^*_{0.n}$ which corresponds to the $f_{0.n}$ strategy's target effort level ($E_{0.n}$) for the age-structured operating model. Suppose that the yield-per-recruit curve as a function of F (fishing mortality) is given by the equation :

$$Y/R = g(F)$$

From the $f_{0.n}$ strategy definition *viz*

$$\left.\frac{dY}{dE}\right|_{E = E_{0.n}} = 0.n \left.\frac{dY}{dE}\right|_{E = 0}$$

it follows that:

$$\left.\frac{d\, g(F)R(F)}{dF}\right|_{F=F^*_{0.n}} = 0.n \left.\frac{d\, g(F)R(F)}{dF}\right|_{F = 0}$$

[where all the relationships shown correspond to a stock at (deterministic) equilibrium for a particular level of fishing mortality or effort.] Note that $F^*_{0.n}$ is not the traditional yield-per-recruit $F_{0.n}$, which is obtained (in effect) by assuming recruitment to be constant.

The "true" $Q_{0.n}$ quota for the age-structured operating model is then given by :

$$Q_{0.n}(n+1) = \sum_{a=0}^{a_{max}} w_{a+1/2} \, S_a \, N_{n+1,a} \, F^*_{0.n} \{1 - e^{-Z_{0.n}}\}/Z_{0.n}$$

where $N_{n+1,a}$ is the number-at-age (for each age) at the beginning of year (n+1) and

$Z_{0.n}$ (= $F^*_{0.n}$ + M) is the total mortality when F = $F^*_{0.n}$.

APPENDIX 7.B: SPECIFICATION OF THE ESTIMATION PROCEDURE-BASED OPERATING MODELS

Note: Units for the parameter estimates quoted below correspond to those for catch and effort given in Tables 7.1 and 7.2.

a) The Babayan *et al.* Operating Model

The Gulland (1961) functional regression approach (see Section 5.5) is used to estimate the parameters of the Fox form of the surplus production function, which are then used to provide the true value of $E_{0.1}$. This amounts to using Geometric Regression (Ricker 1975) to estimate the parameters of the equation

$$(C/E)_i = \alpha\, e^{-\beta \bar{E}_i} \qquad (7.B.1)$$

where $\bar{E}_i$ is the averaged effort (see Chapter 5.5).

The parameter values obtained from this regression when the actual catch effort history for ICSEAF Divisions 1.3 + 1.4 is used, are :

$\hat{\alpha} = 1.1990$

$\hat{\beta} = 0.0015$

The "true" cpue data for this operating model are estimated using the Babayan *et al.* (1986) Linear Method by the formula :

$$(C/E)_i^T = \begin{cases} (C/E)_i \text{ - the actual cpue in year } i & (1965 \le i \le 1975) \\ a + bi \text{ - where } a \text{ and } b \text{ are estimated by a linear fit to the cpue time trend from 1976} & \text{(otherwise)} \end{cases}$$

The estimates of a and b made from the actual cpue data for ICSEAF Divisions 1.3 + 1.4 are:

$\hat{a} = 0.0700$
$\hat{b} = 0.0270$
$\hat{\sigma} = 0.0456$

The residual standard deviation from this linear fit is used to provide an estimate of the observation error for generating the artificial cpue data.

b) The Butterworth-Andrew Operating Model

This operating model is based on the dynamic equation :

$$y_{i+1} = y_i + ry_i\left(1 - \frac{\ln(y_i)}{\ln(K)}\right) - C_i \quad (7.B.2)$$

and the observation model :

$$\widehat{(C/E)}_i = q\left(\frac{y_i + y_{i+1}}{2}\right) \quad (7.B.3)$$

The parameters r, q and K are estimated using $\ln$(cpue) minimisation and the "true" cpue assigned to the estimated cpue series predicted by equation (7.B.3). The parameter values estimated using the actual cpue data series in ICSEAF Divisions 1.3 + 1.4 are :

$\hat{r} = 1.8434$
$\hat{q} = 0.0004$
$\hat{K} = 2985.9$

$\hat{\sigma} = 0.1292$

c) The Lleonart *et al.* Operating Model

This operating model is based on the dynamic equation :

$$\widehat{(C/E)}_{i+1} = \mu.(C/E)_i + (1-\mu)\alpha e^{-\beta E_{i+1}} \qquad (7.B.4)$$

The parameters μ, α and β are estimated using ℓn(cpue) minimisation and the "true" cpue assigned to the estimated cpue series predicted by equation (7.B.4). The parameter values estimated using the actual cpue data series in ICSEAF Divisions 1.3 + 1.4 are :

$\hat{\mu} = 0.6870$

$\hat{\alpha} = 0.8124$

$\hat{\beta} = 0.00097$

$\widehat{(C/E)}_1 = (C/E)_1 = 1.78$

$\hat{\sigma} = 0.1163$

Table 7.1: Values used in the age-structured operating model (see Appendix 7.A) for mass and selectivity at age (a), and annual catches (b).

a) Mass and selectivity at age

Age a	Mass at mid-year* $w_{a+1/2}$(kg)	Age-specific selectivity $S_a = [1+e^{-(a-3)/0.5}]^{-1}$
0	0.020	0.002
1	0.056	0.018
2	0.087	0.119
3	0.177	0.500
4	0.386	0.881
5	0.622	0.982
6	0.834	0.998
7	1.043	1.000
8	1.207	1.000
9	1.333	1.000

*Data source: Butterworth *et al.* (1986a), Table A.V.1.

b) Catch by year

Year Number		Catch** ('000t)
1	(1965)	93.510
2	(1966)	212.444
3	(1967)	195.032
4	(1968)	382.712
5	(1969)	320.430
6	(1970)	402.467
7	(1971)	365.557
8	(1972)	606.084
9	(1973)	377.642
10	(1974)	318.836
11	(1975)	309.374

Year Number		Catch** ('000t)
12	(1976)	389.020
13	(1977)	276.901
14	(1978)	254.251
15	(1979)	170.006
16	(1980)	97.181
17	(1981)	90.523
18	(1982)	176.532
19	(1983)	216.181
20	(1984)	228.672
21	(1985)	211.450

**Data source: Butterworth and Andrew (1987a), Table 3(a).

Table 7.2: Values used for annual effort in the production-model based operating models (see Appendix 7.B).

b) Effort by year

Year Number		Effort** ('000hrs
1	(1965)	52.534
2	(1966)	162.171
3	(1967)	214.321
4	(1968)	398.658
5	(1969)	364.125
6	(1970)	447.186
7	(1971)	420.180
8	(1972)	841.783
9	(1973)	662.530
10	(1974)	708.524
11	(1975)	736.605

Year Number		Effort** ('000hrs)
12	(1976)	926.238
13	(1977)	565.104
14	(1978)	591.281
15	(1979)	425.015
16	(1980)	215.958
17	(1981)	164.587
18	(1982)	333.079
19	(1983)	372.726
20	(1984)	357.300
21	(1985)	320.379

**Data source: Butterworth and Andrew (1987a), Table 3(a).

Table 7.3: The parameters used in testing a selected set of the estimation procedures for robustness to deviations from the original operating model (Appendix 7.A). The values of the parameters α, β and γ have been altered to ensure that K^e, B^e_{MSY}/K^e and MSY are invariant (except in tests 10 to 13, in which some of these quantities have been changed).

	Parameters Altered
1	$\sigma_r = 0.2;\ \sigma_q = 0.2$
2	$M = 0.2$
3	$M = 0.4$
4	$M = 0.5$
5	$a_m = 3$
6	$a_m = 5$
7	$a_r = 4$
8	$\delta = 0.25$
9	$\delta = 1.0$
10	MSY = 200
11	MSY = 300
12	$B^e_{MSY}/K^e = 0.3$
13	$B^e_{MSY}/K^e = 0.45$
14	$N_{1,a} = N_{0,0}\ e^{-aM}\ e^{\varepsilon_y}\quad \varepsilon_y \sim N(0;\sigma_r^2)$

8 REVIEW OF PREVIOUS MODEL SELECTION INVESTIGATIONS

8.1 Introduction

During the last decade, several investigations have been made into the accuracy and precision with which certain of the estimation procedures described in Chapter 5 are able to estimate management variables. The techniques used for this purpose can be divided into three groups: (a) the analytical approach, (b) analysis of the historical record of predictive ability and (c) the operating model approach, each of which is described below. At the end of the Chapter, a summary of some of the problems associated with the continuous equilibrium assumption and with Gulland's (1961) regression approach is given. In the following discussion, $(C/E)_i$ is denoted by U_i for notational simplicity. Appendix 8.A. contains a summary of the estimation procedures that are mentioned in this Chapter.

8.2 The analytical approach

The most complete analytical analysis of bias has been performed by Uhler (1979), who computed the bias in the parameter estimates produced by using a simple process error estimator when the true underlying situation is a discrete Schaefer model with both process and observation error. The underlying situation is thus :

$$y_{i+1} = y_i + ry_i + by_i^2 - C_i + u_i \qquad u_i \sim N(0;\sigma_u^2) \qquad (8.1)$$

$$C_i = qE_i \cdot y_i + v_i \qquad v_i \sim N(0;\sigma_v^2) \qquad (8.2)$$

$$U_i = C_i/E_i \tag{8.3}$$

Estimation of the parameters r, b (= -r/K) and q requires transformation of the system [i.e. equations (8.1) to (8.3)] into a process error estimator by assuming that the observation equation (8.2) is exact (i.e. $\sigma_v = 0$). By substituting equation (8.2) for C_i, replacing y_i by U_i/q [from equations (8.2) and (8.3)] and dividing by U_i, an equation which is linear in the parameters can be obtained :

$$(U_{i+1} - U_i)/U_i = r + (b/q)U_i - qE_i + s_i \tag{8.4}$$

The parameters can now be estimated using multi-linear regression (Draper and Smith 1966). The stochastic term s_i is assumed to be independent of U_i and E_i, so that if the problem caused by the time series nature of the data [in particular, U_i appears on both sides of equation (8.4)] can be ignored, the estimates are unbiased with minimum variance (Draper and Smith *op. cit.*). Uhler (*op. cit.*) evaluates s_i explicitly by taking both of the noise terms in equations (8.1) to (8.2) into account. Substituting equation (8.2) for C_i in equation (8.1) gives :

$$y_{i+1} = y_i + ry_i + by_i^2 - qE_i \cdot y_i + v_i + u_i$$

i.e. :

$$(y_{i+1} - y_i)/y_i = r + by_i - qE_i + e_i \tag{8.5}$$

where $e_i = (v_i + u_i)/y_i$. Thus, even if the true values of $\{y_i\}$ (the time series of biomasses) are known without error, minimum variance estimates of the parameters of equation (8.5) cannot be obtained using standard multi-linear regression, as e_i is not independent of y_i. In addition, one of the independent variables, y_i, appears on both sides of equation (8.5), and this could bias the estimates.

Dividing equation (8.3) by equation (8.2) provides an expression for U_i:

$$U_i = qy_i + w_i \qquad (8.6)$$

where $w_i = v_i/E_i$. Uhler (*op. cit.*) shows that substituting equation (8.6) into equation (8.5) gives :

$$U_{i+1}/U_i = \beta_0 + \beta_1.U_i + \beta_2.E_i + \phi_i \qquad (8.7)$$

where $\beta_0 = (1 + r)$,

$\beta_1 = b/q = -r/(qK)$,

$\beta_2 = -q$ and

$\phi_i = (-2b/q)w_i - (1 + a)w_i/U_i + (U_ib/q)w_i^2 + qv_i/u_i + w_{i+1}/U_i$.

Thus U_i is correlated with ϕ_i. Equation (8.7) is not identical to equation (8.4), as ϕ_i is neither normally distributed nor independent of U_i and E_i (as s_i is assumed to be). According to Uhler (*op. cit.*), the effect of this is to bias the least squares estimates of β_0, β_1 and β_2. The magnitudes of these biases are, however, dependent on the size of σ_w^2.

Uhler (*op. cit.*) additionally investigates the bias when the underlying situation is the continuous rather than the discrete Schaefer model, i.e. :

$$\frac{dy_t}{dt} = ry_t + by_t^2 - C_t + u_t \qquad u_t \sim N(0;\sigma_u^2) \tag{8.8}$$

$$C_t = qE_t.y_t + v_t \qquad v_t \sim N(0;\sigma_v^2) \tag{8.9}$$

$$U_t = C_t/E_t \tag{8.10}$$

Substituting equation (8.9) into equation (8.8) and dividing by y_t gives :

$$\frac{1}{y_t}\frac{dy_t}{dt} = r + by_t - qE_t + (u_t + v_t)/y_t \tag{8.11}$$

which can be integrated over year n to produce :

$$\ell n(y_{n+1}/y_n) = r + b\bar{y}_n - q\bar{E}_n + \bar{\varepsilon}_n \tag{8.12}$$

where $\bar{\varepsilon}_n = \int_n^{n+1} (u_t + v_t)/y_t \, dt$

Replacing y_t by $(U_t - w_t)/q$ and $\bar{y}_t$ by $(\bar{U}_t - \bar{w}_t)/q$ in equation (8.12) then gives :

$$\ell n\left(\frac{U_{t+1} - w_{t+1}}{U_t - w_t}\right) = r + (b/q)(\bar{U}_t - \bar{w}_t) - q\bar{E}_t + \bar{e}_t \tag{8.13}$$

Uhler (*op. cit.*) shows that expanding equation (8.13) (using Taylor's method) yields the result :

$$\ell n(U_{t+1}/U_t) = a_0 + a_1.\bar{U}_t + a_2.\bar{E}_t + \theta_t \tag{8.14}$$

where $a_0 = r$,

$a_1 = b/q = -r/(qK)$,

$a_2 = -q$ and

$$\theta_t = \bar{e}_t + w_{t+1}/U_{t+1} - w_{t+1}^2/U_{t+1}^2 + w_t/U_t - w_t^2/U_t - b/q\bar{w}_t$$

The use of ordinary least squares estimation would thus result in biased estimates of the parameters r, b and q. Uhler (1979) suggests that care should be taken when simple models (with simple minimisation criteria) are used in complex situations, and advocates the use of generalised linear regression in order to minimise the effects of the serial correlation.

Walters (1985) notes that unless an estimation procedure specifically incorporates a bias correction factor, the serial correlation between the errors and the independent variable (due to the time series nature of the data) will always result in biased parameter estimates, no matter how realistic the underlying model itself may be. For example, if recruits are to be regressed against spawners, there will be correlation between the number of spawners in year (i+1) and the number of recruits in year i. Although Walters (*op. cit.*) has derived a bias correction factor for the Ricker stock-recruitment model (equation 8.A.8), such derivations are generally very difficult and tedious.

Walters and Ludwig (1981) show that failure to take measurement error into account in an estimation procedure may also result in biased estimates. For the case of the Ricker stock-recruitment model (equation 8.A.8) in particular, the parameter b_1 tends to be positively biased, resulting in a negatively biased estimate of MSYL, which may lead eventually to biological overexploitation. Walters and Ludwig (*op. cit.*) conclude that all fisheries data sets should be examined for obvious measurement errors and suggest techniques (Walters and Ludwig *op. cit.*) whereby such errors can be corrected.

8.3 Historical record of predictive ability

Several authors have used the accuracy with which model-estimation procedures are able to fit real data sets as a standard by which to assess the usefulness of a procedure (usually using some form of cross-validation). Three types of approach are encountered in the literature:

(i) Stepwise prediction: the estimation procedure is given all the available data and a statistic based on the difference between the observed and predicted data over the whole history of the fishery is computed and compared for the different model estimation procedures.

(ii) Omnibus prediction: the data are divided into two groups; the model is fitted to the first, and predictions of the second group are made. A statistic based on the difference between the observed and predicted values for this second group is computed and compared.

(iii) Revised omnibus prediction: the estimation procedure is given the data up to year i and predicts the data for year (i+1). Prediction of the data for years (k+1) to n can be made, where n is the length of the data series and k is the first year in which the data series is long enough for estimation of the model parameters to be feasible (and reasonable).

The fits of different model estimation procedures may also be assessed by comparing their standard deviations σ, which are estimated (by analogy with linear models) as follows :

$$\hat{\sigma}^2 = SS/(n-p) \qquad (8.15)$$

where SS is the minimum value of the functional (5.3),

n is the number of terms in this functional and

p is the number of model parameters.

Examination of these σ values allows a comparison to be made between estimation procedures based on models which have differing numbers of parameters. A slightly more rigorous approach is to select from all those estimation procedures which have the same number of parameters, that with the smallest SS. The log-likelihood ratio test (Draper and Smith 1966) is then used to select the best procedure from those with differing numbers of parameters, although this test is only exact when the models are linear in their parameters.

Butterworth and Andrew (1987a) compare estimation procedures with respect to the residuals obtained from the model fit (i.e. to the difference between the observations and the corresponding values predicted by the model), and propose that any model for which significant systematic trends in the residuals can be identified, be rejected as being mis-specified. In order to implement this, Butterworth and Andrew (*op. cit.*) use a Runs test (Draper and Smith 1966) to compare the three estimation procedures currently used by ICSEAF for the management of the hake stocks and report that, for all Divisions, the Gulland (1961) estimator (equation 8.A.4) provides fits to the cpue data which are significantly unsatisfactory [see Butterworth and Andrew (*op. cit.*), Table 2]. Although it is unlikely that the data series will be sufficiently long, it is possible to determine the most appropriate minimisation criterion (see Chapter 3) by testing which of these provides homoscedastic residuals. Butterworth and Andrew (*op. cit.*) also use revised omnibus prediction of cpue and $E_{0.1}$ for comparing the three procedures.

Stocker and Hilborn (1981) use revised omnibus prediction with the statistic $(1 - D/\sigma^2)$, which is similar to the square of the correlation coefficient r^2, where :

$$\sigma^2 = \frac{1}{(n-15)} \sum_{i=16}^{n} (C_i - \bar{C})^2$$

and $$D = \frac{1}{[(n+1) - 16]} \sum_{i=16}^{n} (C_i - \hat{C}_i)^2$$

[One would expect the degree of freedom correction applied to D to depend on the number of parameters estimated in order to obtain $\hat{C}_i$, but this does not appear to be the case.] This statistic is used by these authors to compare four production-model estimation procedures [the discrete Schaefer estimation procedure (equation 8.A.3), the Schaefer form of Gulland's (1961) regression (equation 8.A.4) the Pella-Tomlinson (1969) model as formulated by Fox (1975) (equation 8.A.6) and the linearised Schnute-77 estimation procedure (equation 8.A.5)], and three estimation procedures based on time series methods:

(a) catch per unit effort is the same as last year, i.e. :

$$\hat{U}_{i+1} = U_i \text{ or } \hat{C}_{i+1} = U_i \cdot E_{i+1}$$

(b) catch is a random variable with a mean and variance, i.e. :

$$\hat{C}_{i+1} = (C_1 + C_2 + \ldots + C_i)/i$$

(c) an autoregressive method :

$$C_{i+1} = p_1 \cdot E_{i+1} + p_2 \cdot C_i + p_3 \cdot C_{i-1} + p_4 \cdot C_{i-2}$$

Five stocks are used to provide data for these comparisons :

(i) the Northern Hecate Strait Rock Sole: for this stock (which appeared at that time to be in equilibrium, with serially correlated cpue), the stock production models are unable to improve on the simple $\hat{U}_{i+1} = U_i$ method

(ii) the Middle Hecate Strait Rock Sole: for this stock (which has an initial declining cpue phase, followed by an increasing phase), the Gulland (1961) method shows no improvement on its performance for (i), although the other methods all fare better and are able to account for 50% of the observed variation in catch

(iii) the Hecate Strait English Sole: the cpue data for this stock are closely grouped, with no long runs of serially correlated cpue; as a result, the best performance is produced by the discrete Schaefer procedure and the worst by the $\hat{U}_{i+1} = U_i$ method

(iv) the Eastern Pacific Yellowfin Tuna: as the cpue data for this stock likewise show no serial correlation, the $\hat{U}_{i+1} = U_i$ method again gives the worst performance

(v) the Pacific Salmon: this stock shows strong serial correlation in its cpue series, and thus invokes the best performance from the $\hat{U}_{i+1} = U_i$ method.

Although they suggest the use of the linearised Schnute-77 process error estimator and the linear Schaefer model, Stocker and Hilborn (*op. cit.*) warn caution that success in prediction depends on the stock itself and that many of the complex methods cannot predict the following year's cpue better than merely using the current year's cpue value.

Roff (1983) uses the mean absolute percentage error (MA%E) for assessing the accuracy of a fit, and postulates that a potentially useful estimation procedure (with regard to management) is one for which the MA%E is less than 20%. This statistic is defined as :

$$\text{MA\%E} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{C_i - \hat{C}_i}{C_i} \right| \times 100\% \qquad (8.16)$$

No account is taken in his study of the "error due to estimation" (see above), however (i.e. the MA%E can readily be reduced by the use of a model with additional parameters).

Roff (*op. cit.*) proposes the use of the Simple Autoregressive (SA) model to predict future catches, based on the observation that most demersal species comprise many age classes, with the result that neither recruitment nor fishing can substantially alter the population size over a short period of time [i.e. the cpue in year i is approximately equal to the cpue in year (i-1)]. Catches may thus be modelled by the equation :

$$C_i = a + bE_i.C_{i-1}/E_{i-1} \tag{8.17}$$

Table 8.1 summarises Roff's results following his application of stepwise and omnibus prediction testing to 20 stocks in which the Schnute-77 (q estimated) process error estimator (S7-S-PEU) (equation 8.A.9) and the SA model are used to predict catches. Using a chi-squared test (χ^2=5, df=1, P < 0.05), Roff (*op. cit.*) shows that the two models differ significantly with respect to their performance, and explains this difference by showing that the Schnute-77 estimation procedure can be written approximately (Appendix 8.B) as :

$$C_i \approx E_i.C_{i-1}/E_{i-1} \tag{8.18}$$

The fit between catch and effort is thus constrained by the Schnute-77 model to pass through the origin (as would be expected biologically) but, by relaxing this constraint, the SA model is more general and (in cases when the data do not appear to justify this constraint) provides far more accurate estimates.

Roff (*op. cit.*) compares the precision with which the Deriso (1980) process error estimator (equation 8.A.2) and the SA model are able to predict cpue and reports that the two estimation procedures perform similarly, even when Pacific halibut data [the stock chosen by Deriso (*op. cit.*) to illustrate his model] are used. He argues that the conclusion of Stocker and Hilborn (1981) [that the Schnute-77 (q estimated) process error estimator (S7-S-PEU) (equation 8.A.9) is useful in many contexts] is not supported by his findings, and suggests that caution be used when applying it for management purposes. He also suggests that the Deriso (1980) process error estimator (equation 8.A.2) may require the estimation of too many parameters from too few data points, and that this approach is likely to yield erroneous results unless auxiliary information can be obtained.

8.4 The operating model approach

This approach, which is essentially the same as the testing procedure described in Chapter 7, falls into two categories: operating models based on production models and those based on age-structured models.

Uhler (1979) uses the discrete Schaefer model [equations (8.1) to (8.3)] as an operating model. Fixing the effort series $\{E_i : i = 1 .. n\}$ and calculating the true biomass using equation (8.1), he then generates a number of cpue series $\{U_i^R : i = 1 .. n\}$ from equations (8.2) and (8.3). Using an estimation procedure based on the discrete Schaefer model [equation (8.7)], he notes that, although the estimates of r and q obtained are positively biased and those of b negatively biased, the estimates obtained for MSY are almost unbiased. This implies that estimates of certain functions of the parameters may be unbiased, although the parameter estimates themselves are not.

Mohn (1980) reports the results of an investigation into the accuracy with which estimation procedures based on the continuous Schaefer model [the Schaefer continuous equilibrium approach (equation 8.A.1), Gulland's (1961) regression (equation 8.A.4) and the Schnute-77 (q estimated) process error estimator (S7-S-PEU) (equation 8.A.9)] are able to estimate management variables when using an operating model based on the continuous Schaefer model with time delay in the density dependent term, i.e. :

$$\frac{dy(t)}{dt} = ry(t)[1 - \frac{y(t - t_m)}{K}] - qE_t y(t) \tag{8.19}$$

In his study, several 30-year series of artificial cpue data were generated by integration of equation (8.19), using a Runge-Kutta technique. In order to simulate the development of a fishery followed by its collapse, "true" effort was generated by the formula $[0.5 + \sin(\pi t/30)]E_{MSY}$. Observation error was added to the catch-effort data only, according to the formulae :

$$E_t^R = E_t[1 - \varepsilon_i^R] \qquad \varepsilon_i^R \text{ from } N(0;\sigma^2)$$

and (8.20)

$$C_t^R = C_t[1 - \eta_i^R] \qquad \eta_i^R \text{ from } N(0;\sigma^2)$$

where σ^2 was chosen to give 95% confidence regions of 5%, 10% and 20% for this error (Mohn *op. cit.*). In order to investigate the behaviour of the estimation procedures for different stocks, a stock with high productivity was simulated by choosing $r = 0.6$ and $(C/E)_1 = 0.6$, and a stock with low productivity with $r = 0.2$ and $(C/E)_1 = 1.2$. The estimation procedures were given both smoothed and unsmoothed cpue data (where smoothing was achieved by the method described in Chapter 5).

Mohn (*op. cit.*) reports that the C/E *vs* E regression produced biases in excess of 100% in some cases, their sign depending on whether the data originated from the development phase or recovery phase of the fishery.

Smoothing of the cpue data series appeared to decrease this bias. The Gulland (1961) regression method performed substantially better, managing to estimate both MSY and E_{MSY} with greater accuracy and precision. The Schnute-77 procedure was unbiased (it is very similar, in a sense, to the operating model used, anyway), but was unable to estimate the parameters in a few of the runs, owing to failure of the nonlinear optimisation algorithm. This indicates that the Schnute-77 procedure is likely to be relatively imprecise. Pre-smoothing of the cpue data again reduced the number of failures.

Ludwig and Walters (1985) use the Deriso (1980) process error estimator (equation 8.A.2) as an operating model. Cpue data similar to the ICSEAF hake data sets were generated, and the Deriso process error estimator and the Ricker model (equation 8.A.8) used as estimation procedures. In order to simulate an environment in which auxiliary information is available when using the Deriso estimator, only α_1 and β_1 in the stock recruitment relation, and q were estimated; the other parameters were assumed to be known exactly. Ludwig and Walters (*op. cit.*) report that the Ricker model is more successful at estimating E_{MSY} in many cases. When the Deriso (1980) procedure was used to estimate ℓ and ρ in addition to α_1, β_1 and q, many simulations converged to physically impossible parameter values. The authors conclude that their results are a reflection of the bias-variance trade-off (discussed in Chapter 3).

Hilborn (1979) investigates the performance of a number of management algorithm-estimation procedure combinations. He defines an age-structured operating model which incorporates density dependent recruitment and a number of noise terms; further, he defines two variants of this operating model, one reflecting a slow-growing long-lived species and the other a more productive species. The general (Hilborn) operating model defines the stock dynamics as :

$$N_{a+1,i+1} = N_{a,i} \cdot S \tag{8.21}$$

where S is the adult survival rate. The number of recruits in year i, $N_{1,i}$ is defined :

$$N_{1,i} = \frac{mZ_i}{(h + Z_i)^{\gamma}} e^{v_i} \qquad v_i \sim N[0;(0.2)^2] \tag{8.22}$$

where Z_i is the number of eggs produced in year i and is calculated as follows :

$$Z_i = \sum_{j=4}^{20} N_j \cdot f_j \tag{8.23}$$

Here f_j is the number of eggs produced by each animal aged j years, calculated using the formula :

$$f_j = \begin{cases} 0 & \text{if } w_j < w_T \\ (w_j - w_T)d & \text{if } w_j > w_T \end{cases} \tag{8.24}$$

where w_j is the mass of an individual aged j years and w_T is the mass below which no eggs are produced.

Five years of cpue data were generated (Hilborn *op. cit.*), assuming alternate years of low and medium effort, and the estimation procedure-management algorithm combinations were subsequently allowed to simulate management of the stock for 50 consecutive years. The sum of the total catch taken and the biomass remaining after this period is used as the index of performance. The value of the index obtained for each of the chosen combinations is compared with that obtained for the fixed escapement policy (Clark 1976) when perfect information about the stock is available. These combinations are :

(a) the discrete Schaefer model (equation 8.A.3) with a linear observation model (i.e. cpue proportional to biomass), using fixed escapement effort regulation,

(b) the discrete Schaefer model (equation 8.A.3) with a nonlinear observation model, using fixed escapement effort regulation,

(c) the discrete Schaefer model (equation 8.A.3) with a nonlinear observation model, using fixed escapement quota regulation,

(d) the Schnute-77 (q estimated) process error estimator (S7-S-PEU) (equation 8.A.9), using fixed escapement effort regulation and

(e) the Schnute-77 (q estimated) process error estimator (S7-S-PEU) (equation 8.A.9), using constant effort regulation.

Hilborn (*op. cit.*) reports that for many of the artificial data sets, the Schnute-77 (equation 8.A.9) and (linear) Schaefer procedures (equation 8.A.3) were unable to estimate any of the parameters when the stock was initially in an equilibrium unexploited state, although when the parameter values estimated were positive, they were generally very close to their "true" values. Starting the cpue series at equilibrium (but not at the unexploited stock size) resulted in fewer failures by these procedures. When the stock was initially overexploited, the estimation procedures were unable, in many cases, to determine that this was the case and the stock consequently failed to recover to higher levels. When the data were generated at more productive stock levels, however, all estimates improved and the number of cases in which overexploitation was overlooked by the estimation procedure decreased.

The policy of fixed escapement with effort regulation provided the largest value of the performance index calculated. The constant effort strategy produced too slow a recovery, thus "wasting" yield, while quota regulation in many cases accidentally led to overexploitation of the stock. Hilborn (*op. cit.*) postulates that the reason for failure of the Schaefer-type estimation procedures is their inability to model an age-structured population. He also observes that when the data contrast increases, the parameters are estimated successfully more frequently.

The International Council for the Exploitation of the Sea (ICES 1987) uses an operating model similar to the age-structured models of Butterworth (1988a) of Hilborn (1979), differing in that noise terms are added to the fecundity (f_i), to the density dependent growth parameter (Υ in Chapter 7 and above), and to the numbers- and catch-at-age data. The data given to the six estimation procedures considered consisted of 10 years of increasing effort followed by 10 years of decreasing effort (the ICES report states that the contrast obtained in this situation is greater and the data are less noisy than is the usual case in fisheries data sets).

Here too, the Schaefer C/E *vs* E regression (equation 8.A.1) produced the least satisfactory performance of all estimation procedures considered, consistently overestimating both MSY and E_{MSY} (ICES *op. cit.*). The Pella-Tomlinson (1969) model [as formulated by Fox (1975)] (equation 8.A.6), was found to have estimated the parameters consistently well, although some nonsensical parameter estimates were obtained as a result of correlation between the parameters. Although the Schnute-77 (q estimated) process error estimator (S7-S-PEU) (equation 8.A.9) estimated MSYL consistently well, it overestimated E_{MSY}, while the Deriso/Schnute procedure (equation 8.A.2) was only able to estimate two parameters, and then only if the starting values were close to the true solutions. When convergence of the non-linear minimisation algorithm did occur, however, its estimates of MSY were reasonable, but their interpretation in terms of absolute biomass were not. The Shepherd (q estimated) process error estimator (Sh-B-PEU) (equation 8.A.10) underestimated both MSY and MSYL consistently, occasionally failing altogether in the presence of observation error (ICES *op. cit.*).

Ludwig *et al.* (1987) compare the performance of the Power (equation 8.A.7) and Ricker (equation 8.A.8) TLS estimation procedures in terms of the accuracy and precision of their estimates of the optimal effort [i.e. that effort which maximises the expected present value of the resource (see Chapter 4 for more details on economic management methods)]. One hundred simulated data sets, each consisting of 25 years of artificial catch and effort data, were generated. The Ricker model was found to show consistently better performance than the Power model, even when the data were generated by the latter, suggesting that some surplus production functional forms may provide more robust estimators than do others.

8.5 Discussion of the approaches used for assessing estimation procedures

Of the three different approaches described above, the operating model approach appears to be the most useful when attempting to select a set of estimation procedures for application to a particular stock. This method may be extended naturally to assess the performance of management algorithm-estimation procedure combinations [e.g. the scheme proposed by the International Whaling Commission (IWC 1987) for assessment of the performance of management procedures utilising cpue data and absolute abundance estimates]. This approach is problematic, however, in that it can only be used when large and powerful computing facilities are available; as a result, it is unlikely that it can be ported easily to a microcomputer, in line with the current trend at ICSEAF [see ICSEAF (1987)]. Further, the results obtained are specific to the particular situation investigated, and it may be difficult to establish whether they hold in general.

The analytical approach, by its nature requiring complex mathematics, can only be applied to simple estimation procedures. The complexity of the analysis rapidly increases with that of the estimation procedure under consideration. It is unlikely, for example, that an analysis such as that of Uhler (1979) would be possible if the Fox rather than the Schaefer form of the surplus production function were to be used in the estimation procedure. The usefulness of this technique as an aid to selecting an estimation procedure for application to a particular resource is therefore limited. Its use may, however, clarify the (statistical) reasons why a particular estimation procedure is unlikely to be successful.

Comparison of the fit of different estimation procedures to a particular data set provides a quick and easy method of assessing their usefulness. This method has certain disadvantages, however, which seem to have escaped the notice of its proponents in some instances. These include the following:

(a) Although the fit to the historic data may be good ("the error due to approximation" is sufficiently small), the "error due to estimation" may nevertheless be substantial; a good fit does not alone necessarily imply good predictive ability. Few authors have investigated this source of error to date.

(b) Investigating the performance of an estimator on a large number of (real) data sets may produce confusing results, particularly if the ultimate function of the "best" procedures is to provide estimates of management variables for one particular resource only.

(c) Daniel and Wood (1971) have shown that techniques for identifying the existence of systematic trends in the residuals (such as the Runs test) may be inadequate for small data sets. In addition, there is a problem with rejecting procedures which produce fits that show systematic trends in their residuals. This is because genuine auto-correlation effects (which could be a consequence of serial correlation in causal environmental factors) could lead to a model being rejected immediately if a method such as the Runs test is used, and also because the presence of process error tends to produce auto-correlation in the residuals of an observation error estimator.

The poor performance of the cpue *vs* E regression reported in a number of the studies discussed above is perhaps not surprising, owing to the fact that effort appears in both the dependent and independent variables. An implicit negative correlation between these two variables therefore exists, resulting (even if the correlation is near zero) in an MSY estimate which is close to the average historical catch and which may bear no resemblance to the true MSY (Knights and Pope 1975, Sissenwine 1978, Ricker 1973, Polacheck and Hilborn 1988). In addition, even when no observation error exists, MSY and E_{MSY} will be overestimated (Polacheck and Hilborn *op. cit.*, Andrew 1986, Butterworth and Andrew 1987a). One of the reasons for this is that, for a declining stock, the E_i in an observed $[E_i,(C/E)_i]$ data pair reflects not only that effort required to maintain the stock at a biomass corresponding to $(C/E)_i$, but also that (further) effort required to make the additional catch producing the observed decline in the biomass (Andrew *op. cit.*, Butterworth and Andrew *op. cit.*). A further problem which leads to confusion is that the correlation coefficients for such regressions are usually high, indicating a good fit, and this is misleading in the light of the effects mentioned above (Polacheck and Hilborn 1988, Roff and Fairbairn 1980).

Gulland's (1961) procedure also performs badly in a number of the studies. The basis for this procedure lies in the premise that if recruitment is constant (in a yield-per-recruit sense), then the average effort over the fishable life of a cohort should reflect its relative abundance. A possible reason why many of the operating model approaches indicate that this method is poor, is that they assume implicitly that recruitment decreases as effort increases (because increasing effort usually corresponds to decreasing biomass). Although this procedure compensates in the correct direction for the non-equilibrium state of a resource, it is not clear whether the magnitude of this adjustment is appropriate (Roff and Fairbairn 1980). Use of Gulland's procedure may lead to confusion because, like any procedure based on the continuous equilibrium assumption, it provides (in almost all cases) estimates of management variables which appear reasonable, even when the data are clearly not able to estimate them (Polacheck and Hilborn 1988).

Roff and Fairbairn (*op. cit.*) and Sissenwine (1978) criticise Gulland's method because effort appears in both the independent and dependent variables in the regression of cpue against a moving average of effort. In theory, the correlation between two variables X_i and $1/X_i$ will be reduced if X_i is replaced by a moving average of its previous and current values, as long as the X_i's are themselves uncorrelated. In many fisheries, however, the time series of effort $\{E_i\}$ on a species is auto-correlated (Roff and Fairbairn *op. cit.*), even when moving averages over 10 years are used [although it is possible that multiplying $1/E_i$ by C_i (with its associated noise component) may reduce the correlation coefficient]. Roff and Fairbairn (*op. cit.*) report a correlation between C/E and $\bar{E}$ as well as between E and $\bar{E}$ for many of the 20 stocks in their investigation. If this is the case in general, an apparent relationship between C/E and $\bar{E}$ as estimated by this procedure (and a high associated correlation coefficient) may be merely a statistical artefact.

APPENDIX 8.A: MODELS USED IN THIS CHAPTER

The following symbols appear in the equations below:

y_i - the biomass at the beginning of year i

C_i - the catch in year i

E_i - the fishing effort in year i

U_i - the cpue in year i

r - the intrinsic growth rate

K - the equilibrium unexploited population size

q - the catchability coefficient

a) The CPUE *vs* E regression

$$(C/E)_i = a + bE_i \tag{8.A.1}$$

where a and b are parameters of the linear regression.

b) The Deriso (1980) process error estimator

$$\begin{aligned} U_{i+1} = {} & (1+\rho)e^{-M}(1-qE_i+m)U_i \\ & - e^{-2M}\{\rho(1-qE_i)(1-qE_{i-1})+(1-\rho)^2(1-qE_{i-1})m + \rho m^2\}U_{i-1} \\ & + (1+\rho)\rho e^{-3M}m(1-qE_{i-2})(1-qE_{i-1}+m)U_{i-2} \\ & - (\rho e^{-2M})^2 m^2(1-qE_{i-2})(1-qE_{i-3})U_{i-3} \\ & + q(1-m)F\{1-qE_{i+1-k}\cdot U_{i+1-k}/q\} \end{aligned} \tag{8.A.2}$$

where ρ is the Brody growth coefficient,

M is the natural mortality rate,

k is the age of recruitment into the fishery, m is the fraction of juvenile fish not recruiting into the fishery in year (i+1) and

F is the stock-recruitment relation [here taken to be that of Ricker (1954)]

$$U_{i+1-k}/q \exp(\alpha_1-\beta_2 U_{i+1-k}/q)$$

where α_1 and β_1 are parameters of the production function.

c) The Discrete Schaefer model

$$\frac{U_{i+1}}{U_i} - 1 = r - \frac{r}{qK} U_i - qE_i \tag{8.A.3}$$

d) The Gulland (1961) procedure

$$\widehat{(C/E)}_i = a + b \bar{E}_i \tag{8.A.4}$$

where a and b are parameters of the linear regression.

e) The Linearised Schnute-77 process error estimator

$$\ell n(\frac{U_{i+1}}{U_i}) = r - q(\frac{E_{i+1} + E_i}{2}) - \frac{r}{qK} (\frac{U_i + U_{i+1}}{2}) \tag{8.A.5}$$

f) The Pella-Tomlinson (1969) model

$$\hat{C}_{i+1} = \bar{E}_{i+1} (\frac{Kq^{m-1}}{H} + \frac{q^m \bar{E}_{i+1}}{H})^{1/m-1} \tag{8.A.6}$$

where m is a skewness parameter,

H is a production model parameter and

$\bar{E}_i$ is the averaged effort (see Section 5.8).

g) The observation error form of the Power model

$$\begin{aligned} y_{i+1} &= a_1 (y_i - C_i)^{b_1} \\ \hat{C}_i &= y_i(1 - e^{-qE_i}) \end{aligned} \tag{8.A.7}$$

where a_1 and b_1 are parameters of the production function.

h) The observation error form of the Ricker model

$$\begin{aligned} y_{i+1} &= (y_i - C_i)e^{a_1 - b_1(y_i - C_i)} \\ \hat{C}_i &= y_i(1 - e^{-qE_i}) \end{aligned} \tag{8.A.8}$$

where a_1 and b_1 are parameters of the production function.

i) The Schnute-77 (q estimated) process error estimator

$$\hat{C}_i = \frac{qKE_i}{r} \ell n[1 + \frac{A}{B} \frac{(e^B - 1)}{(1 - e^A)} (1 - e^{-D})] \tag{8.A.9}$$

where $A = r - qE_{i-1}$,

$B = r - qE_i$ and

$D = rC_{i-1}/(qKE_{i-1})$.

j) The Shepherd (q estimated) process error estimator

$$\widehat{(C/E)}_{i+1} = (C/E)_i \left[\frac{a'}{1 + (a'-1)(C/E)_i/qK} - 1\right] - qC_i \tag{8.A.10}$$

where a' is a parameter of the production model.

APPENDIX 8.B: PROOF OF EQUATION 8.18

The Schnute-77 process error estimator (equation 8.A.9) may be written as follows :

$$C_i = \frac{qKE_i}{r} \ln[1 + \frac{A}{B} \frac{(e^B - 1)}{(1 - e^A)} (1 - e^{-D}) e^{\varepsilon_i}] \qquad (8.B.1)$$

where $A = r - qE_{i-1}$,

$B = r - qE_i$,

$D = rC_{i-1}/(qKE_{i-1})$ and

ε is a noise term.

Note that if $|a| < 0.7$, then $e^a \sim (1 + a)$ and $\ln(1+a) \sim a$. If catch and effort are normalised so that $0 < C_i < 1$ and $0 < E_i < 1$ (Roff 1983), then, since $|r - qE| < 1$ (if $r > q$ and $r < 1$), A, B and D are likely to be small, so that :

$$C_i \approx \frac{qKE_i}{r} \ln[1 + \frac{AB}{BA}(1 - e^{-D}) e^{\varepsilon_i}] \qquad (8.B.2)$$

$$\approx \frac{qKE_i}{r} \ln[1 + De^{\varepsilon_i}] \qquad (8.B.3)$$

If e^{ε} is "small" then :

$$C_i \approx \frac{qKE_i De^{\varepsilon_i}}{r} = \frac{qKE_i}{r} \cdot \frac{rC_{i-1}e^{\varepsilon_i}}{qKE_{i-1}} \qquad (8.B.4)$$

$$\hat{C}_i \approx E_i(C_{i-1}/E_{i-1})$$

Table 8.1 : Summary of the comparison between the Schnute-77 (q estimated) process error estimator (S7-S-PEU) and the Simple Autoregressive (SA) model in terms of the accuracy with which each is able to estimate catches for 20 different stocks. Results are summarised from Roff (1983).

Method	Schnute-77		SA Model	
	Lowest MA%E	MA%E < 20%	Lowest MA%E	MA%E < 20%
Stepwise	1	6	19	12
Omnibus 3 Years	5	5	15	11
Omnibus 10 Years	*	4	*	7

* Not given

9 RESULTS

9.1 General presentation

The Tables in this Chapter and those in the Appendices contain estimates (in some cases a subset of these) of the percentage bias of the estimates of E_{MSY}, MSY, Q_{MSY}, $E_{0.1}$ and $Q_{0.1}$ produced by the estimation procedures considered for particular operating models. For a quantity A that has a constant "true" value (such as E_{MSY}, MSY and $E_{0.1}$) and is estimated by method M, the value given in the Tables for the percentage bias estimate is :

$$100\ [\bar{\hat{A}}^{M} - A^{\text{"true"}}]/A^{\text{"true"}} = 100\ \widehat{B}^{M}(A) \qquad (9.1)$$

where $\bar{\hat{A}}^{M} = \{\sum_{R=1}^{R_{max}} \hat{A}_R^{M}\}/R_{max}$ and

$R_{max} = 250$ for the results shown.

For a quantity whose "true" value does change between simulations (such as Q_{MSY} and $Q_{0.1}$ when the Butterworth age-structured operating model is used with $\sigma_r \neq 0$), this value is :

$$100\ \widehat{B}^{M}(A) = \frac{100}{R_{max}} \sum_{R=1}^{R_{max}} [\hat{A}_R^{M} - A_R^{\text{"true"}}]/A_R^{\text{"true"}} \qquad (9.2)$$

The standard error (s.e.) of the estimated percentage bias is given in parenthesis. For a quantity A, this is equal to :

$$100\ \{\sum_{R=1}^{R_{max}} [([\hat{A}_R^{M} - A_R^{\text{"true"}}]/A_R^{\text{"true"}}) - \widehat{B}^{M}(A)]^2/[R_{max}(R_{max} - 1)]\}^{1/2}$$

The coefficient of variation (expressed as a percentage) of the mean of the set of $\{\hat{A}_R^M\}$ values, where $A_R^{\text{"true"}}$ is constant across the simulation data sets:

$$100 \left\{ \sum_{R=1}^{R_{max}} [\hat{A}_R^M - \overline{\hat{A}^M}]^2 / [R_{max}(R_{max} - 1)] \right\}^{1/2} / \overline{\hat{A}^M} \tag{9.3}$$

can be obtained from the estimate of the s.e. of the estimated percentage bias by multiplying by the factor :

$$A^{\text{"true"}} / \overline{\hat{A}^M} \tag{9.4}$$

The value given in the Tables for the percentage estimated expected discrepancy is :

$$100 \hat{\Delta}^M(A) = \frac{100}{R_{max}} \sum_{R=1}^{R_{max}} \left| \hat{A}_R^M - A_R^{\text{"true"}} \right| / A_R^{\text{"true"}} \tag{9.5}$$

Entries in these Tables marked with the symbol "+" are not significantly different from zero at the 5% level, as calculated from their s.e.'s (and assuming normality). In these cases, this analysis has thus not produced significant evidence of bias of the associated model estimation procedures and they have therefore been assumed to be unbiased estimators of the management related quantities concerned, for the particular operating model and combination of noise terms under consideration. Percentage biases and expected discrepancies estimated to be in excess of 1000% are marked with the symbol "*", while entries with a double question mark ("??") represent procedures which could not provide estimates for one or more of the artificial data sets, owing to the failure of the method used to estimate the model parameters. [The possible reasons for this include attempting to calculate the natural logarithm of a negative number, and failure of the non-linear minimisation algorithm to find a minimum (possibly caused by the sum of squares surface (SS) being nearly flat near the initial estimates)].

In order to simplify the presentation of results in the Tables and Appendices, acronyms have been used in some Tables in place of the full descriptions of estimation procedures. Appendix 9.A describes the construction of these acronyms.

9.2 Preliminary investigation of the bias of the model estimation procedures currently in use by ICSEAF

Table 9.1 contains the estimated percentage bias of the estimates of $E_{0.1}$ and $Q_{0.1}$ produced by the three estimation procedures currently used by ICSEAF for the management of hake stocks (Bn-F-GLU, BA-F-OK and Ll-F-PEU) when the estimation procedures themselves are used as operating models (see Appendix 7.B). For the results reported in this section, all noise is observational.

According to Ratkowsky (1981), a bias of more than 1% is worth noting. By this criterion, therefore, all the estimation procedures investigated, with the exception of the Butterworth-Andrew (Fox form) y_1 = K observation error estimator (BA-F-OK) - in the remainder of this section referred to as the Butterworth-Andrew procedure - when used with the Butterworth-Andrew operating model, clearly yield notably biased estimates for all of the operating models considered. Unlike the Butterworth-Andrew procedure, the other procedures are unable to produce unbiased estimates for both the $Q_{0.1}$ and $E_{0.1}$ management variables. (With one exception, these estimated biases are statistically significantly different from zero.) The most important of these biases are those of $Q_{0.1}$ for the Lleonart *et al.* (Fox form) q estimated (with unsmoothed cpue data) process error estimator (Ll-F-PEU) - for the remainder of this section referred to as the Lleonart *et al.* procedure - when used with the Lleonart *et al.* operating model, and those of $E_{0.1}$ for the Babayan *et al.* (Fox form) Linear Method (with unsmoothed cpue data) procedure (Bn-F-GLU) - for the remainder of this section referred to as the Babayan *et al.* procedure - when used with the Babayan *et al.* operating model. The biases on the diagonals of Tables 9.1(a) and (b) represent the "error due to estimation" that is reflected as bias rather than variance. These biases are rather disturbing, as they indicate that even if the latter procedures are exact representations of the underlying fishery, they are still unable to provide unbiased estimates of the management variables.

The variation in the estimates provided by the Lleonart *et al.* procedure (relative variance levels can be inferred from the s.e.'s of the estimated bias, which are shown in Table 9.1) is by far the largest for the estimation procedures considered (about four times greater than that for the other estimation procedures, except when the Babayan *et al.* operating model is used), which is consistent with the findings of Butterworth and Andrew (1987a) concerning the relative inefficiency of this estimator. All the estimation procedures yield highly variable estimates when the Babayan *et al.* operating model is used to generate the artificial data sets. In general, the Babayan *et al.* estimation procedure produces the least satisfactory estimates in terms of size of bias; for both $Q_{0.1}$ and $E_{0.1}$ the average absolute bias over the operating models considered is about 20%.

Observed values for the skewness and excess kurtosis (kurtosis - 3) of the distributions of the estimates of the management variables $E_{0.1}$ and $Q_{0.1}$ are given in Tables 9.2 and 9.3. These are compared with their expected value (of zero) for a normal distribution, by noting that estimates of skewness have variance $6/R_{max}$ and of excess kurtosis, $24/R_{max}$ (Ratkowsky 1981), so that the extent to which the distributions of $\hat{E}_{0.1}$ and $\hat{Q}_{0.1}$ differ from the normal can be determined. The Lleonart *et al.* procedure and all three estimation procedures when the Babayan *et al.* operating model is used, produce estimates which are markedly and often significantly non-normal (particularly in terms of skewness) in most cases. This implies that the distributions of $\hat{E}_{0.1}$ and $\hat{Q}_{0.1}$ are unlikely to be normally distributed when real data are used; the traditional simple method of estimating 95% confidence intervals by ±2 s.e.'s (i.e. using standard intervals) is thus likely to produce biased estimates. Given the number of simulations carried out (R_{max} = 250), the precision of these estimates of skewness and excess kurtosis is low (s.e.'s of 0.15 and 0.31 respectively); Ratkowsky (1981) recommends a larger number of simulations (±1000) for obtaining precise estimates of these quantities.

These preliminary results indicate that the performance of the three estimation procedures currently used by ICSEAF may be poor, and it is therefore vital to determine whether any other production-model-type estimation procedures are able to perform better. In addition, it is important to use a more realistic operating model which more accurately reflects the underlying stock dynamics than any of these three simple production models, in order to obtain a better picture of the relative performance of the estimators.

9.3 Selection between model estimation procedures

9.3(a) General comments

In order to select those model estimation procedures which are most likely to perform best, the estimated biases of the estimates of E_{MSY}, MSY, Q_{MSY}, $E_{0.1}$ and $Q_{0.1}$ produced by each estimation procedure when using the Butterworth age-structured operating model were calculated. The three combinations of error types described in Chapter 7 were used in turn to generate the artificial data sets for this purpose. These estimates are given in Appendices A to C. Very few of the estimation procedures are, in fact, able to provide unbiased estimates (or, strictly, estimates for which the bias can not be demonstrated to be significantly different from zero) for any of the management variables, while none is able to produce unbiased estimates for all of them, for all three error type combinations considered. Many of those estimation procedures which actually do "succeed" (such as the Babayan *et al.* ARIMA procedures - Bn-F-GAU, Bn-F-GAS, Bn-S-GAU and Bn-S-GAS), do so only because their estimates are highly imprecise [note the large s.e.'s in corresponding entries in Tables A(1) and B(1)], which results in the tests conducted for bias detection having very low power.

The biases of the estimates produced by all of the Babayan *et al.* time series approaches [with the exception of the Adaptive (Lag 0) (with unsmoothed cpue data) procedures (Bn-F-GOU and Bn-S-GOU)] increase with increasing values of σ_r, indicating that Gulland's (1961) method of estimating the parameters is the more appropriate (although not necessarily the more accurate, nor the most appropriately applied to the hake stocks in the ICSEAF Convention Area) when the dominant noise is observational. These procedures appear always (i.e. for all error type combinations considered) to provide positively biased estimates of management variables, as has been previously noted by Butterworth and Andrew (1987a). Bias is, of course, dependent on the underlying operating model, and Appendix A shows that the biases [Tables A(1), A(4) and A(7)] for the three current ICSEAF procedures considered in Section 9.2 (BA-F-OK, L1-F-PEU and Bn-F-GLU) are larger than the corresponding biases in Table 9.1. There is thus substantial "error due to approximation" as well as "error due to estimation" (measured in part by the biases in Table 9.1) in these procedures. It is not possible, however, to determine the exact ratio between "error due to approximation" and "error due to estimation" from the comparative bias estimates in these Tables because bias is only one component of the "error due to estimation" (the other being variance).

The Babayan-Kizner and Butterworth-Andrew approaches, although based on essentially the same model, have very different statistical properties. While the Babayan-Kizner (Fox form) procedures are able to provide less biased estimates of $E_{0.1}$, E_{MSY} and MSY than the comparable Butterworth-Andrew procedures, their estimates of $f_{0.1}$ and f_{MSY} quotas have very large (generally greater than 40%) biases. As a result, the Butterworth-Andrew procedures tend to give better overall performance [see Tables A(3), A(4), B(3), B(4) and C(3), C(4))].

Most of the Lleonart *et al.* process error estimators are able to provide estimates which have biases of less than 20%, making these the most accurate procedures. The corresponding observation error estimators are, however, unable to provide reasonable estimates [see Table C(8)], especially the Schaefer form (y_1 estimated), which shows biases in excess of 1000% for all management variables considered. The procedures based on the Shepherd model are apparently unable to provide estimates which have biases smaller than 40% [see Tables A(10), B(10) and C(10)], especially when $\sigma_q = 0$ and $\sigma_r = 0.3$ [see Table C(10)], and are thus completely unsuitable for use in the management of the hake resources in the ICSEAF Convention Area.

The relative amount of variation in the estimates provided by the different procedures can be inferred from the s.e.'s of the estimated biases shown in Appendices A to C. The Horbowy-Draganik procedures and the process error estimators which estimate α, for example, show relatively high variance, while variation in the estimates produced by process error estimators which use the Linear Method of estimating α, and by observation error estimators which assume $y_1 = K$, is much smaller. The very small s.e.'s noted for the Schnute-85 procedure [Tables A(11), B(11) and C(11)] are suspicious and merit further investigation [see comments in Section 10.1(d)].

9.3(b) Initial model selection

In order to select the estimation procedures to be used in the second stage (robustness) tests, the following algorithm is employed:

i) All procedures which have, for any of the error combinations investigated, an estimated bias larger than 40% for any of the management variables, are rejected. (Even though some of these large biases are not shown to be significantly different from zero, the low power of the associated test would be indicative of unacceptable imprecision in the estimator concerned.)

ii) Any procedure which has a low bias but high variance is rejected. The reason for this is that an estimate of the expected discrepancy for such a procedure, were it to be made, would always be large, as variance is a major contributor to the size of the discrepancy estimate.

iii) The remaining procedures are divided into groups according to their underlying model and surplus production functional form, and the procedure within each group which consistently shows the smallest biases is selected.

Table 9.4 contains a summary of the application of this algorithm to the 106 estimation procedures considered. As sometimes an entire category of estimation procedures may be rejected [e.g. the Babayan *et al.* (Fox form) time series approaches], the algorithm has been altered so that at least one estimation procedure from each category is selected (excluding the category of very biased estimation procedures based on the Shepherd model). Table 9.5 lists the 16 procedures used in the second stage (robustness) tests.

9.3(c) Second stage (robustness) testing

Appendix D gives the estimates and s.e.'s of the estimated biases when the 17 robustness tests (Table 7.3) are applied to the 16 estimation procedures selected. The estimated expected discrepancies of $Q_{0.1}$ for the 17 robustness tests are given in Appendix E and a summary of these results is presented in Table 9.6.

The Babayan *et al.* time series, Babayan-Kizner, Horbowy-Draganik, Schnute-85 and Butterworth-Andrew (Fox form) procedures are the least robust to changes made in the operating model parameter values (which are set out in Table 7.3), showing biases and discrepancies in excess of 40% for some of the management variables. Other procedures, such as the Butterworth-Andrew (Schaefer form) Linear Method (using smoothed cpue data) process error estimator (BA-S-PLS) and the Lleonart *et al.* (Schaefer form) $(C/E)_1 = qK$ (using unsmoothed cpue data) process error estimator (Ll-S-PFU) perform very well for some of the quantities but very poorly for others. The BA-S-PLS procedure, for example, has a low average rank of 2.53 for MSY [Table 9.6(b)] but a high average rank of 11.00 for E_{MSY} [Table 9.6(a)]. Of the procedures considered, those based on the Fox form of the surplus production function clearly perform very poorly in comparison with those based on the Schaefer form. Tests in which the ratio B_{MSY}/K is altered produce the largest differences in the biases obtained, indicating that this quantity is particularly critical in determining the robustness of an estimation procedure.

Six procedures [the Butterworth-Andrew (Schaefer form) $y_1 = K$ observation error estimator (BA-S-OK), the Butterworth-Andrew (Schaefer form) $y_1 = K$ TLS estimator (BA-S-TK), the Lleonart *et al.* (Fox form) Linear Method (with smoothed cpue data) process error estimator (Ll-F-PLS), the Schnute-77(1) $y_1 = K$ observation error estimator (S71-S-OK), the Schnute-77(2) y_1 = K observation error estimator (S72-S-OK) and the Schnute-77 $(C/E)_1$ = qK (with smoothed cpue data) process error estimator (S7-S-PFS)] show the best performances overall.

Table 9.7 contains a summary of the estimated expected discrepancies for the estimates of $Q_{0.1}$ produced by the six procedures selected above, for the 17 robustness test variants of Butterworth's age-structured operating model. It is clear that the Schnute-77(1) procedure performs the least satisfactorily of the six, and also that the particular version of this procedure which is based on integrating the continuous form of the population dynamics equation (S72-S-OK) gives a better performance in all but one case (B_{MSY}/K = 0.3). Except in three cases, the Butterworth-Andrew (Schaefer form) y_1 = K TLS estimator (BA-S-TK) consistently shows the best performance of the six. The improvement achieved by this procedure for the pure process error case (σ_q = 0; σ_r = 0.3) is substantial and even the Lleonart *et al.* procedure (Ll-F-PLS), which is based on the assumption of process error, is unable to match it. The failure (in relative terms) of the BA-S-TK procedure when the error structure is pure observation error is understandable, as the other procedures (except for Ll-F-PLS) assume that only observation error exists. The performance of the Schnute-77 $(C/E)_1$ = qK (using smoothed cpue data) process error estimator (S7-S-PFS), although slightly poorer than that of the BA-S-TK procedure, is in general superior to that of the rest. The particular variant of the Butterworth age-structured operating model which results in the highest average expected discrepancy for the six best procedures is the (a_r = 4) case.

9.3(d) Robustness of the estimated biases and discrepancies to the number of simulation trials

In order to determine whether the estimated biases and expected discrepancies are strongly dependent on the number of simulations, estimates of the bias and expected discrepancy for the 17 variants of the Butterworth age-structured operating model were made, using first 500 and then 1000 simulations, for three of the six model estimation procedures which showed the most satisfactory performances. Tables 9.8 and 9.9 report the estimates of the expected discrepancies obtained from these simulations. These estimates and the corresponding estimated biases (not shown in the Tables) are similar to those obtained when only 250 simulations were used, but (as expected) the size of the s.e.'s of the estimated expected discrepancies diminish as the number of simulations increases. (The s.e. is inversely proportional to the square root of the number of simulations.) The original number of simulations (i.e. 250) thus appears to be adequate in order to obtain reasonably precise estimates of bias and expected discrepancy.

9.3(e) Comparison of the model estimation procedures with the deterministic version of the Butterworth age-structured operating model

Figure 9.1 shows the biomass trend predicted by three observation error estimators [the Schnute-85 $y_1 = K$ (S8-F-OK), Butterworth-Andrew (Schaefer form) $y_1 = K$ (BA-S-OK) and Schnute-77(1) $y_1 = K$ (S71-S-OK) observation error estimators] from deterministic data ($\sigma_r = \sigma_q = 0$) generated by the Butterworth age-structured operating model. These

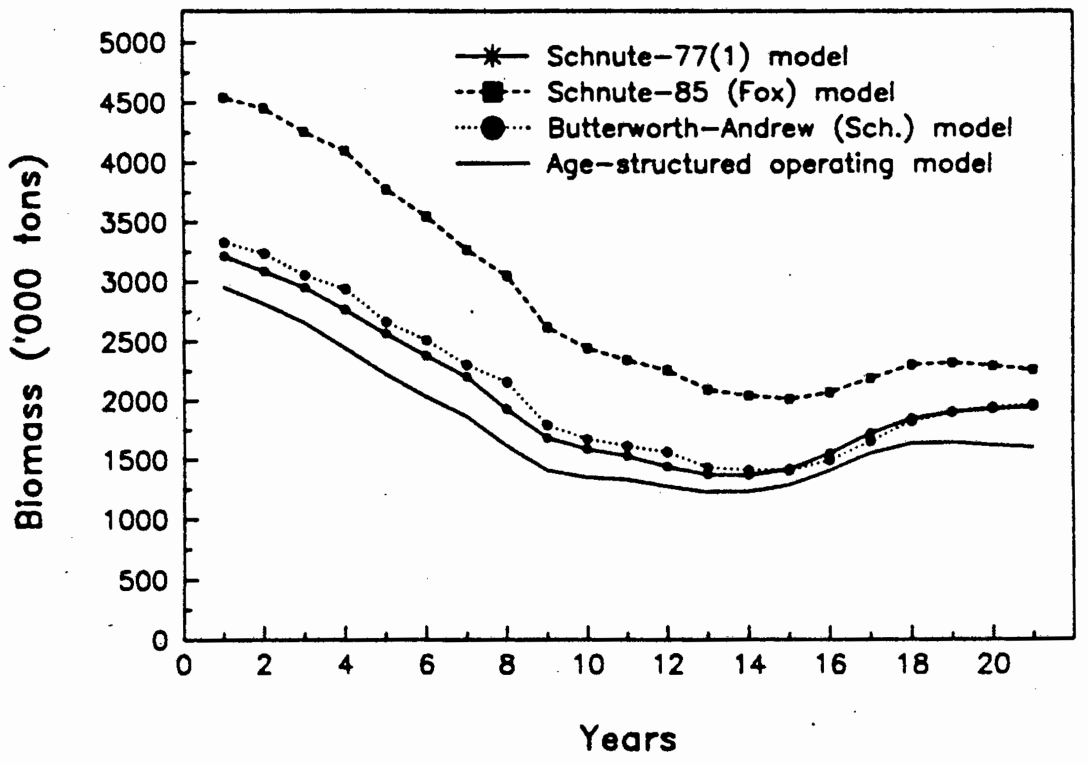


Figure 9.1: Comparison of the "true" biomass time-series produced by the (deterministic) age-structured operating model with the biomasses estimated by three selected observation error estimators (see text), from data generated by the age-structured operating model in the absence of error ($\sigma_r = \sigma_q = 0$).

three procedures clearly overestimate biomass relative to the "true" recruited biomass computed by the operating model, although the latter two are nonetheless able to predict correctly the year in which the declining trend in biomass reverses. Both of these show an ability to reproduce general trends in biomass fairly well and thus manage to estimate reliably the relative change in biomass from the start of exploitation. The reliable estimation of relative changes in biomass by several surplus production-like models used for the management of whale stocks has also been noted by de la Mare and Cooke (1983). This feature may, however (except in the case of the Schnute-85 procedure), be the result of fitting cpue to the mean biomass; as cpue is approximately proportional to ("true") biomass in the Butterworth age-structured operating model, most procedures would be expected to reproduce the biomass trend reasonably accurately.

Figures 9.2 to 9.7 compare the equilibrium yield curve (as a function of effort) estimated from deterministic data by each of six selected estimation procedures [the Babayan *et al.* (Fox form) Linear Method (with unsmoothed cpue data) (Bn-F-GLU), the Butterworth-Andrew (Fox form) y_1 = K observation error estimator (BA-F-OK), the Lleonart *et al.* (Fox form) q estimated (with unsmoothed cpue data) process error estimator (Ll-F-PEU), the Lleonart *et al.* (Fox form) Linear Method (using smoothed cpue data) process error estimator (Ll-F-PLS), the Butterworth-Andrew (Schaefer form) y_1 = K observation error estimator (BA-S-OK) and the Schnute-77(1) y_1 = K observation error estimator (S71-S-OK)], with the corresponding "true" curve for the Butterworth age-structured operating model. This "true" curve is determined by setting a fixed fishing mortality and allowing the age-structure to

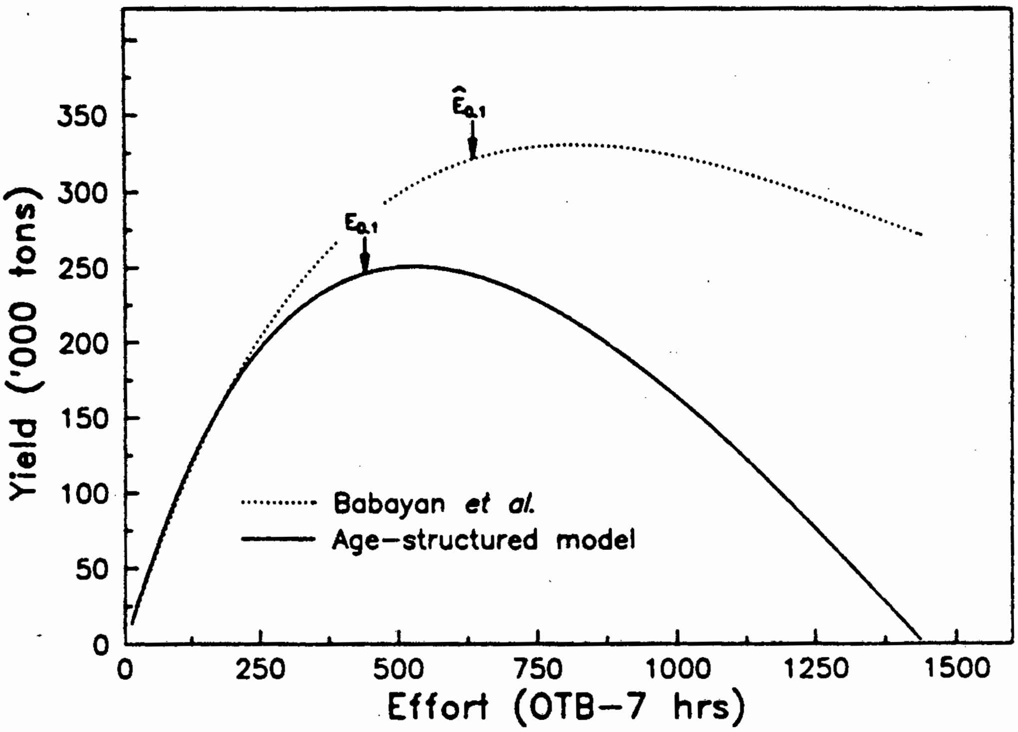


Figure 9.2: Comparison of the "true" equilibrium yield-effort curve for the (deterministic) age-structured operating model with the curve estimated by the Babayan *et al.* (Fox form) Linear Method (with unsmoothed cpue data) procedure (Bn-F-GLU), applied to data generated by the age-structured operating model. The true and estimated values of $E_{0.1}$ are indicated.

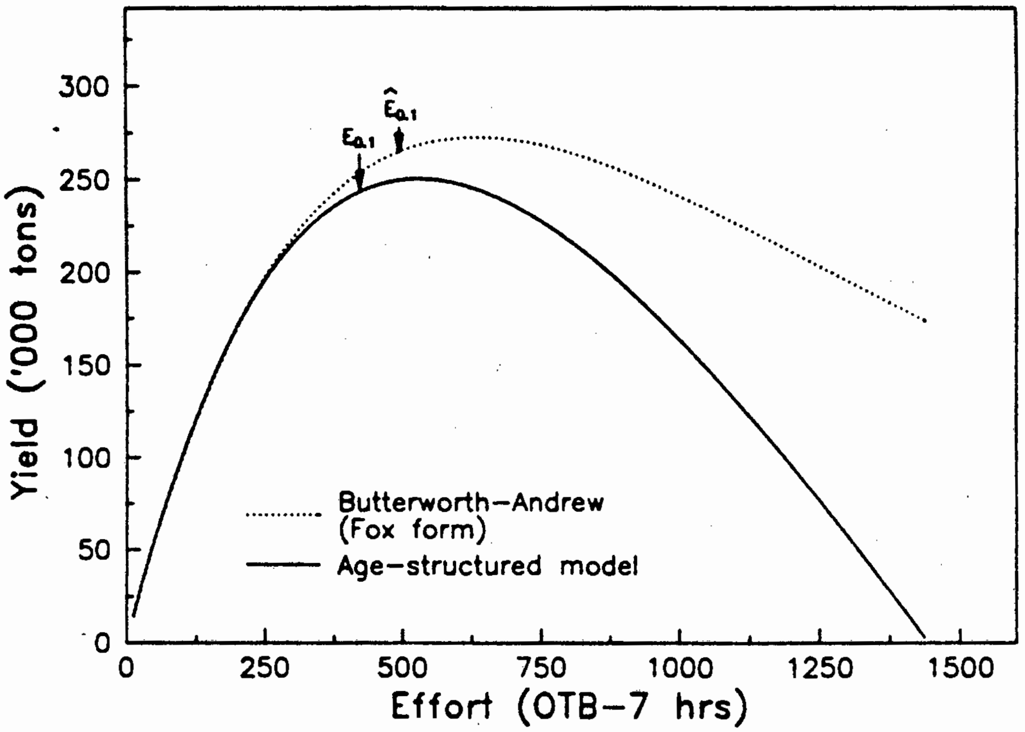


Figure 9.3: Comparison of the "true" equilibrium yield-effort curve for the (deterministic) age-structured operating model with the curve estimated by the Butterworth-Andrew (Fox form) y_1 = K observation error estimator (BA-F-OK), applied to data generated by the age-structured operating model. The true and estimated values of $E_{0.1}$ are indicated.

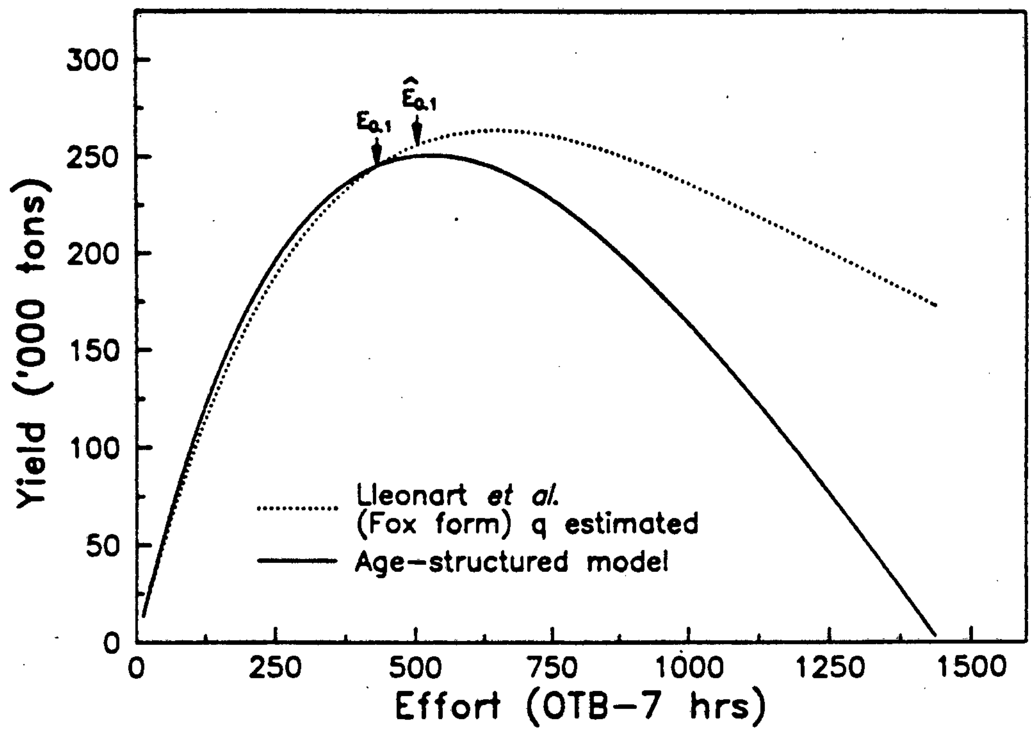


Figure 9.4: Comparison of the "true" equilibrium yield-effort curve for the (deterministic) age-structured operating model with the curve estimated by the Lleonart *et al.* (Fox form) q estimated (with unsmoothed cpue data) procedure (Ll-F-PEU), applied to data generated by the age-structured operating model. The true and estimated values of $E_{0.1}$ are indicated.

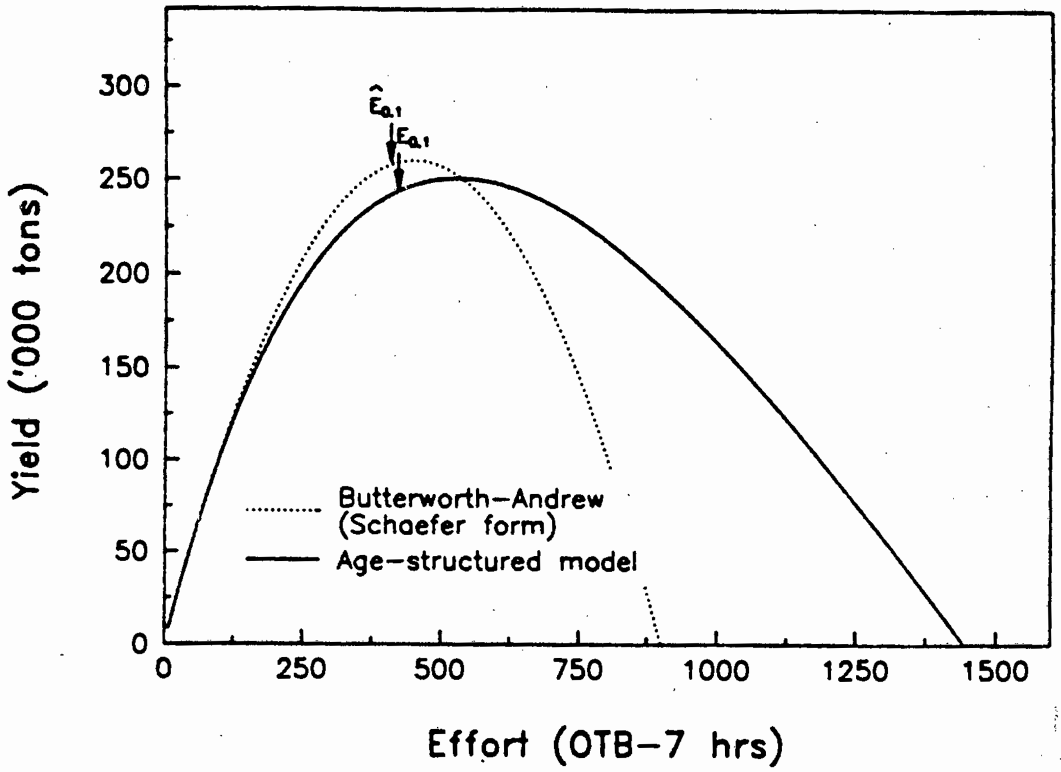


Figure 9.5: Comparison of the "true" equilibrium yield-effort curve for the (deterministic) age-structured operating model with the curve estimated by the Butterworth-Andrew (Schaefer form) y_1 = K observation error estimator (BA-S-OK), applied to data generated by the age-structured operating model. The true and estimated values of $E_{0.1}$ are indicated.

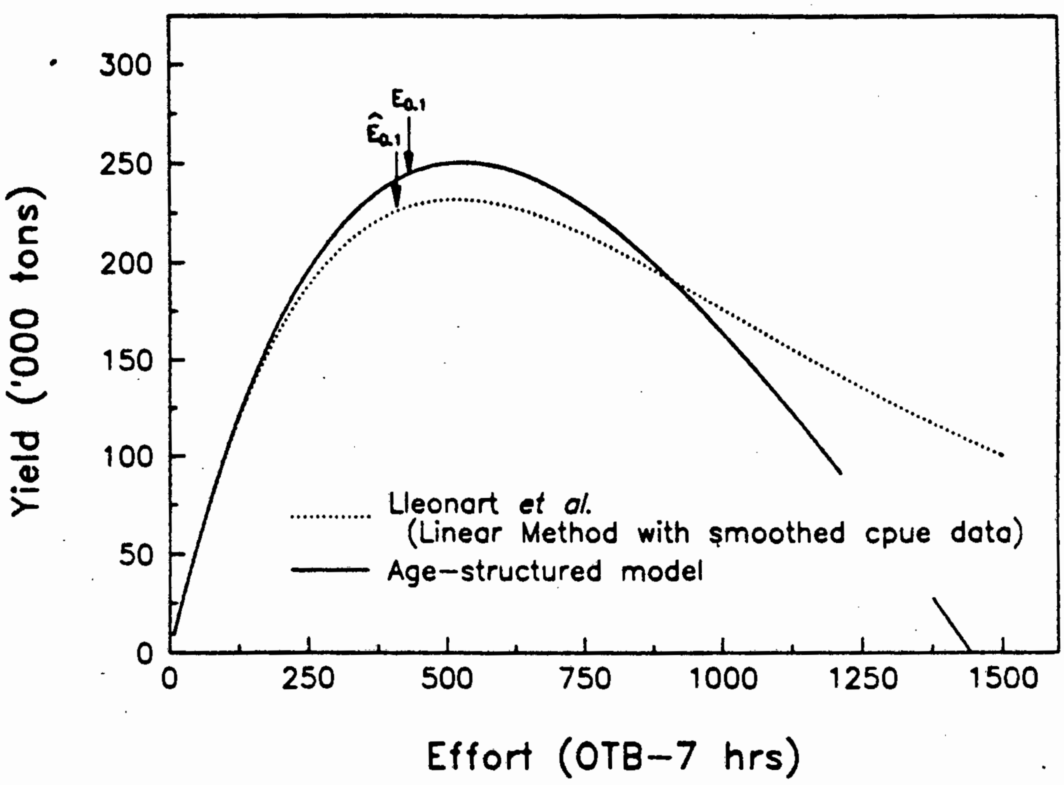


Figure 9.6: Comparison of the "true" equilibrium yield-effort curve for the (deterministic) age-structured operating model with the curve estimated by the Lleonart *et al.* (Fox form) Linear Method (with smoothed cpue data) procedure (Ll-F-PLS), applied to data generated by the age-structured operating model. The true and estimated values of $E_{0.1}$ are indicated.

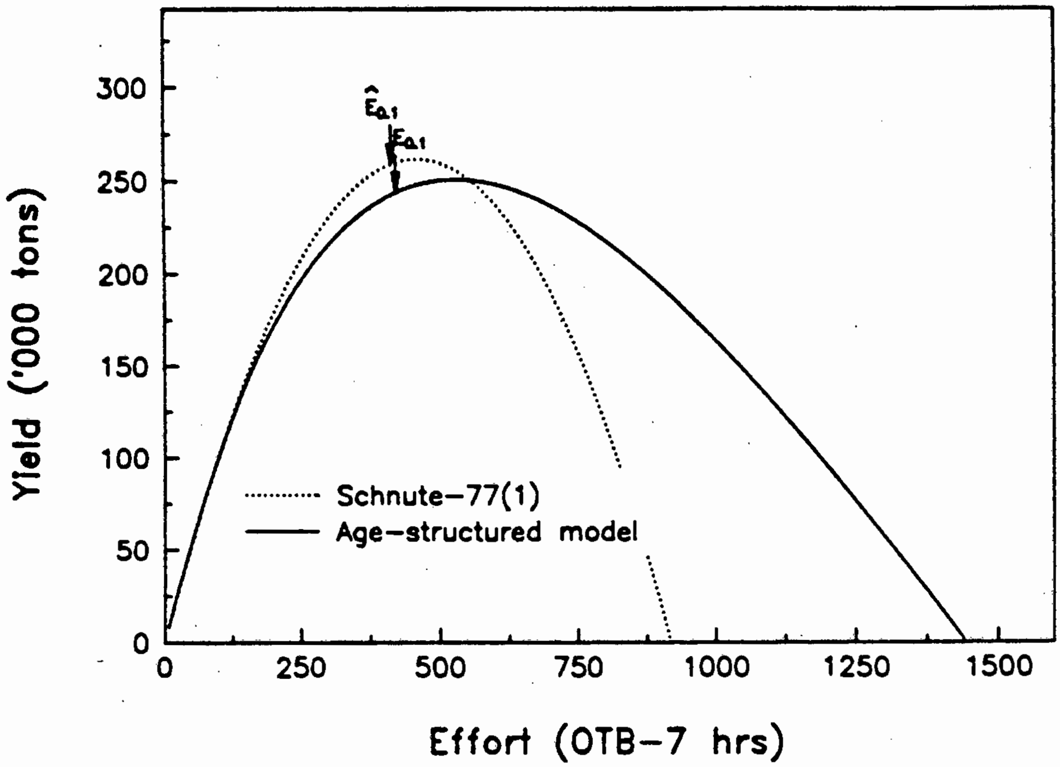


Figure 9.7: Comparison of the "true" equilibrium yield-effort curve for the (deterministic) age-structured operating model with the curve estimated by the Schnute-77 y_1 = K observation error estimator (S71-S-OK), applied to data generated by the age-structured operating model. The true and estimated values of $E_{0.1}$ are indicated.

adjust to the associated equilibrium biomass level. The figures show that the production model estimates of $E_{0.1}$ from the deterministic data are similar (but not identical, because of distribution skewness) to the average values obtained from the stochastic simulations. The positive bias of the deterministic $E_{0.1}$ estimate is clear in most cases. The curves associated with three of the estimation procedures which performed "best" in the simulations (BA-S-OK, L1-F-PLS and S71-S-OK) appear to provide more accurate representations of the "true" curve near $E_{0.1}$ than do the three estimation procedures currently used by ICSEAF (Bn-F-GLU, BA-F-OK and L1-F-PEU).

These results show that production-model-type estimation procedures do exist (six are specifically selected here) which are able to perform better than the three currently in use by ICSEAF for the management of the hake resources. In addition, they indicate that certain groups of estimation procedures (the Babayan *et al.* time series methods and the Shepherd procedures, for example) are quite inappropriate for this purpose and that model estimation procedures based on the Schaefer form of the surplus production function appear to be more robust than those based on the Fox form.

9.4 Some properties of variable estimation

9.4(a) The effect of the reversal of the downward cpue trend

In order to determine the effect of the data contrast provided by the reversal in the downward cpue trend observed, after the late seventies, for the real resource in Divisions 1.3 + 1.4, the testing procedure was implemented using catch and effort data from 1965 to 1979 only. Table

9.10(a) lists the estimated bias in the management variable estimates produced by seven of the estimation procedures which performed well in all of the selection tests, as well as for the Butterworth-Andrew Fox form (y_1 = K) observation error estimator (BA-F-OK). (The latter procedure is included here as it appears to be the one which performs the most satisfactorily of the three in current use by ICSEAF - see Section 9.2.) For all except those estimation procedures based on the Schnute-77 model (see Section 5.11), most of the bias estimates in Table 9.10(a) are substantially greater than the corresponding ones in Appendix B. Increasing the number of years of cpue data by two results in a substantial decrease in bias [Table 9.10(b)]. Further increasing the number of years of data [see Tables 9.10(c) to (e)] produces the following three categories of results :

(a) the biases decrease to an asymptote [as for the Butterworth-Andrew (Fox form) y_1 = K observation error estimator (BA-F-OK) estimates of MSY],

(b) no change in bias is observed (as in the case of management variables estimated by procedures based on the Schnute-77 model),

(c) the biases reach a minimum before 1985 (≈ 1981-1982) and are currently on the increase (as for the BA-F-OK procedure estimates of Q_{MSY}, for example).

Note that the bias estimates produced for the BA-F-OK procedure changes sign when the data point for 1982 is included. Also of note is that the s.e.'s in Tables 9.10(a) to (e) decrease in size as the data series is extended; this corresponds to an increase in estimation precision, implying that the increase in contrast provided by the additional data generally results in a substantial improvement in management variable estimates, although in some cases their bias in fact increases. Tests can be performed which involve varying the length of the data series, as an additional means of checking the robustness of the model estimation procedures to the underlying operating model. Any estimation procedure which shows a lack of robustness to increasing the length of the data series should not be considered for long-term management of the hake resources.

9.4 (b) The effect of "serial correlation" on parameter estimation

The estimated biases and their associated s.e.'s for the simulation of 5, 7 and 10 years of additional, "serially correlated" data (during which the quota was set to that produced by the estimation procedure under consideration - see Chapter 7) are given in Table 9.11. For all the procedures considered here, except those based on the Schnute-77 model, the bias in the estimates of the parameters (especially of MSY) decreases as the number of years of data in the cpue series increases. This is most evident in the biases of the estimates of E_{MSY}, $E_{0.1}$ and MSY produced by the Lleonart *et al.* (Fox form) q estimated process error estimator (Ll-F-PEU), although, in contrast, the bias of the estimates of quotas produced by this estimator increases dramatically with time. (This procedure was included here in order to test whether, given a longer data series, the parameter α may be estimated reliably from the data.)

Again the biases of the estimates produced by procedures based on the Schnute-77 model show no definite trend with respect to magnitude or variation. The s.e.'s of the biases of the estimates produced by the other estimators tend to decrease as the length of the data series is increased, however, indicating an increase in the precision of the estimates of the management variables.

Estimates of the 95% confidence interval for the actual biomass (i.e. that provided by the operating model, as opposed to that estimated by the estimation procedure under consideration) at the start of 1996 (i.e. after 10 years of "serial correlation") produced by six of the estimation procedures are given in Table 9.12. For the calculation of these, the catch in year i (for i > 1985) was set equal to the value either of the quota ($Q_{0.1}$) or of the mass of the exploitable stock in year i - whichever was the smaller. The quota was thus assumed always to have been taken, if possible. The recruited biomass [calculated using the deterministic (σ_r = 0) version of the Butterworth age-structured operating model] at the beginning of this period was 0.55K. It is clear from Table 9.12 that the Babayan *et al.* procedure (Bn-F-GLU), on average, is likely to deplete the stock if used as a method for setting quotas, because the mean "true" biomass computed at the end of the 10-year period is below MSYL (0.39K) This reflects biological overexploitation and the procedure should therefore be rejected. The Lleonart *et al.* (q estimated) (Fox form) process error estimator (Ll-F-PEU) places the stock on average below that biomass (.47K) which corresponds to the equilibrium point for the $f_{0.1}$ strategy. The other procedures considered in Table 9.12 are able to manage the stock in such a way that, at the end of the 10 year period, the stock biomass is close to the target level of 0.47K, on average.

In a further investigation of the effect of using the same model estimation procedure first for assessing the status of a stock and thereafter for setting the quota, the quota during the period of m years of "serial correlation" (see Chapter 7) was set to the arithmetic mean of the quotas produced by the three estimation procedures currently used by ICSEAF. The estimates of the bias of the management variables provided by the Butterworth-Andrew (Fox form) $y_1 = K$ observation error estimator (BA-F-OK) using the (m+n) years of data were then calculated.

If the presence of such "serial correlation" does, in fact, have a detrimental effect on accuracy, the biases in Table 9.13 should be lower than those produced when the BA-F-OK procedure alone is used for assessing the stock and setting quotas. In only two of the 15 cases investigated (Q_{MSY} and $Q_{0.1}$ for 7 years of "serial correlation") is there a significant reduction in bias when the averaged quotas are used, however. The effect of "serial correlation" on the bias of the estimates of management variables therefore does not appear to be substantial in comparison with the biases inherent in the estimation procedures themselves (although this result may not be robust to the length of the period of "serial correlation").

9.5 Variance estimation procedures

9.5(a) Preliminary testing of the variance estimation procedures

The estimated percentage biases and corresponding standard errors of the s.e.'s and c.v.'s of the estimates of $E_{0.1}$ and $Q_{0.1}$ produced by the three model estimation procedures currently used by ICSEAF [the Babayan *et al.* (Bn-F-GEU), Lleonart *et al.* (Ll-F-PEU) and Butterworth-Andrew (BA-F-OK) procedures] are given in Table 9.14. In these simulations the model estimation procedure and operating model were the same. The sizes of the s.e.'s in this Table indicate that the number of simulations (R_{max} = 250) has been sufficient to demonstrate that all the variance estimation procedures tested are notably biased [*sensu* Ratkowsky (1981)], and that these biases are clearly significantly different from zero.

Some of the results obtained indicate biases in the estimation of variances in excess of 1000% (marked with "*"), which seems highly unlikely in the light of previous studies comparing these variance estimation procedures [see Efron (1981)]. The large biases are associated with large variances and may be due to one of two possible factors:

(a) the variance estimation procedure produced a few markedly outlying estimates which could have affected the estimate of bias (the effect of this should decrease as R_{max} is increased), or

(b) the model estimation procedure used (such as the Lleonart *et al.* procedure) may have produced very biased and imprecise estimates of the management variables, which led to failure of the variance estimation procedure.

Possibility (b) above can perhaps supply an explanation for the marked failure of the "naive" bootstrap techniques with the Lleonart *et al.* procedure.

The jack-knife and (conditioned) parametric bootstrap methods provide the most accurate variance estimates for the Butterworth-Andrew procedure, while the (conditioned) parametric bootstrap method is the only procedure which gives reasonable results for the Lleonart *et al.* procedure. The jack-knife technique produces substantially positively biased estimates of variance for this latter approach, as surmised by Butterworth and Andrew (1987a), although no "error due to approximation" is present in this case, as the model estimation procedure and operating model were the same. The fact that none of the variance estimation procedures performs particularly well for the Babayan *et al.* procedure may be a result of high "error due to estimation" (see Section 9.2) associated with this procedure.

The c.v.'s of individual estimates of c.v.'s and s.e.'s (as distinct from the c.v.'s of the means of the s.e. and c.v estimates) are calculated by adjusting the s.e. of the bias given in the Tables by formula (9.4) and then multiplying by 250. In general, the precision of the s.e. and c.v. estimates in Table 9.14 appears to be poorest for the Babayan *et al.* procedure, particularly with respect to its c.v. estimates of $\hat{Q}_{0.1}$, which have coefficients of variation greater than 200% for all the variance estimation procedures tested. By comparison, the c.v.'s of the s.e. and c.v. estimates for management variable estimates produced by the Butterworth-Andrew procedure range from 19% to 54%. The variance estimates produced by the (conditioned) parametric bootstrap method can be improved by restricting the error added to the observed $(C/E)_i$'s in equation (6.17). Essentially, this involves restricting σ to a more reasonable range instead of automatically using the estimate provided by equation (6.18), which is occasionally very large. When this technique (with the restriction $\sigma \le 0.13$) is applied to the Babayan *et al.* procedure, the c.v. estimate for $\hat{Q}_{0.1}$ improves from having an estimated positive bias of 740% to having an estimated negative bias of 71%, i.e. a bias comparable with that of the corresponding $E_{0.1}$ estimate. The improved variance estimates produced by this technique are summarised in Table 9.15.

As the c.v. of an estimated s.e. is inversely proportional to the square root of the number of Monte-Carlo trials performed, an improvement in performance might be expected by increasing this number. However, when the trials are increased from 250 to 1000 (see Table 9.15) and σ is adjusted as described in the previous paragraph, the percentage bias in the s.e . of $\hat{E}_{0.1}$ decreases by only 0.08%. Any further increase in the number of trials is unlikely to be advantageous, as the resulting decrease in this bias appears to be marginal and accompanied by a similarly marginal change in the precision of the variance estimate. This is very surprising, as the c.v. of the mean of the estimated c.v.'s is proportional to the inverse of the square root of the number of simulations; the c.v. of the bias was therefore expected to be halved. The most probable explanation for this failing to occur is that the Babayan *et al.* procedure's fits to the data are generally very poor and this, in turn, possibiy leads to a higher probability of obtaining outlying estimates of variance - and hence a decrease in the expected precision of the estimates of the s.e.'s.

Although some procedures [e.g. the (conditioned) parametric bootstrap and jack-knife] perform relatively well here, this may be an artefact of the model estimation procedure being the same as the operating model used. It is thus important to determine how well the variance estimation procedures perform when the Butterworth age-structured model is used as the operating model.

9.5(b) Testing of variance estimation procedures using the Butterworth age-structured operating model

Table 9.16 contains a summary of Appendices F to H, which list the estimated bias and its standard error for the estimates of the s.e., c.v. and 95% confidence interval for the estimates of $\hat{E}_{0.1}$ produced by the three model estimation procedures tested above. These entries represent the average of the estimated biases for the three error combinations considered. The artificial data sets were generated by the Butterworth age-structured operating model. The corresponding results for $\hat{Q}_{0.1}$ are not shown, as they are less accurate because the "true" 95% confidence interval for the estimates of $\hat{Q}_{0.1}$ was estimated using the Linear Method (see Chapter 7). This method is unlikely to provide an unbiased estimate as it assumes that the confidence interval is symmetric, which is highly unlikely when the estimates of skewness computed in Section 9.2 are considered.

Here again, some of the results indicate biases in excess of 1000% (indicated by "*" in Table 9.16), notably for the "naive" and *ad hoc* bootstrap procedures. The small bias obtained (Table 9.16) when using the ("naive") permuted bootstrap method to estimate the variance of the management variable estimates produced by the Butterworth-Andrew procedure is the result of averaging large positive and large negative biases and is not a reflection of good performance. The information matrix method failed completely for the Butterworth-Andrew procedure (BA-F-OK) as, during at least one of the simulations for each noise combination, it was not possible to compute the variance of the parameters due to the attempted inversion of a near singular matrix. When this method does provide estimates, these are not particularly accurate.

Three variance estimation procedures (the jack-knife and the two conditioned bootstrap methods) perform best in estimating the s.e. and c.v. of $\hat{E}_{0.1}$ produced by all three model estimation procedures considered. As before, variance estimates for the Butterworth-Andrew procedure (except for the case $\sigma_q = 0$, $\sigma_r = 0.3$ - see Appendix H) have smaller bias than those for the other procedures. None of the six variance estimation methods in Table 9.14 and the 10 in Appendices F to H performs well for the Babayan *et al.* procedure (Bn-F-GLU). Biases of large magnitude (both positive and negative) are evident in Table 9.14 as well as in the Tables in these three Appendices.

The results in Appendices F to H illustrate how critically the accuracy of variance estimation depends on the selection of the appropriate error distribution. For the Butterworth-Andrew procedure, for example, the biases of the three best variance estimation procedures increase substantially as the difference between the "true" error structure (imposed by the operating model) and the error structure underlying the model estimation procedure (pure observational, in this case) increases. When the "true" error is all observational (Appendix F), the largest absolute bias in the s.e.'s of $\hat{E}_{0.1}$ produced by for three best variance estimation procedures is 10.15% (jack-knife), but when the "true" error is all process error (Appendix H), the smallest absolute bias is 74.77%.

The estimates of the s.e. and c.v. of $\hat{E}_{0.1}$ for the three best variance estimation procedures tend to be negatively biased, although the estimates of s.e.'s and c.v.'s produced by the jack-knife method for the Lleonart *et al.* (Ll-F-GLU) procedure are consistently larger than those corresponding to the two other model estimation procedures when the same variance estimation procedure is applied. This (generally negative) bias results in estimated confidence intervals being smaller than is actually the case (i.e. the lower limit is positively biased and the upper limit negatively biased). Estimates of lower and upper 95% limits are generally more accurate than those of s.e.'s or c.v.'s, however [see entries for the Butterworth-Andrew procedure in Appendices F(3), F(4), G(3) and G(4)].

These simulations indicate that the jack-knife and (conditioned) bootstrap methods perform the best of the 10 variance estimation procedures considered. As the other variance estimation procedures are likely to provide highly biased and often very imprecise estimates, they should be rejected and are thus not considered in the final testing stage.

9.5 (c) Performance of the variance estimation procedures with three of the best model estimation procedures

Table 9.17 is a summary of Appendices I to K, which contain the estimated bias and estimated expected discrepancy and associated standard errors for the estimates of the s.e. and c.v. of $\hat{E}_{0.1}$ and $\hat{Q}_{0.1}$, and for the 95% confidence limits of $\hat{E}_{0.1}$ for three of the model estimation procedures which performed best in the simulation tests [the Butterworth-Andrew (Schaefer form) y_1 = K observation error estimator (BA-S-OK), Lleonart *et al.* (Fox form) Linear Method (using smoothed cpue data) process error estimator (Ll-F-PLS) and the Schnute-77(1) (y_1 = K) observation error estimator (S71-S-OK)]. The artificial data sets were generated by the Butterworth age-structured operating model. (The 95% confidence limits for $\hat{Q}_{0.1}$ are less accurate, for the reasons given above, and are not shown.)

The three variance estimation procedures generally perform equally well for these three model estimation procedures, although the estimated expected discrepancies obtained for the Ll-F-PLS procedure are generally larger. Again the most accurate results are produced when the noise is all observational (see Appendix I), and here too, incorrect estimation of the "true" underlying error distribution results in large estimated discrepancies (see Appendices J and K). The s.e. estimates are again generally negatively biased. In one of the simulations for the case of pure process error as the "true" error distribution, the

S71-S-OK procedure combined with the (conditioned) parametric bootstrap failed, possibly as a result of attempting to calculate the logarithm of a negative number or the exponential of a large positive number. Although checks in the computer program used to compute variance estimates exist to prevent such eventualities occurring, the nature of the Schnute-77 model (see equation 5.36) may allow certain combinations of r, q and K to cause this type of error. The BA-S-OK procedure also failed for this error structure (it has a bias of over 1000%) because in one of the simulation trials a highly biased estimate of variance occurred, which substantially influenced the average bias and expected discrepancy.

When the data up to 1979 only are used (Table 9.18), the biases and discrepancies increase substantially and are less precisely determined. The S71-S-OK procedure again suffers the least from the shorter data series and the BA-S-OK procedure the most. The relative performance of the three variance estimation methods in combination with any of the three model estimation procedures is not considerably altered.

In order to determine whether "serial correlation" (see Chapter 7) substantially affects the variance estimation procedures, the same tests were performed after including 10 years of "serial correlation". The estimated biases and expected discrepancies are given in Table 9.19. These are generally not substantially larger than the corresponding quantities in Appendix J (the operating model with mixed error structure) for the data series at its original length. In fact, the (conditioned) parametric bootstrap method appears to improve slightly for the longer data series.

APPENDIX 9.A: ACRONYMS FOR MODEL ESTIMATION PROCEDURES USED IN THIS THESIS

In order to simplify the presentation of the results, the names of the model estimation procedures have been replaced by acronyms in some of the Tables following this Appendix and in some of the Appendices themselves. Each of these acronyms is constructed from distinct mnemonics, separated by dashes, representing :

1) the model upon which the estimation procedure is based,
2) the form of the surplus production function used and
3) the method used to estimate the model parameters.

The acronym BA-F-OK, for example, represents the Butterworth-Andrew (Fox form) y_1 = K observation error estimator.

The following mnemonics are used to represent the different models (part 1 of each acronym) :

Butterworth-Andrew	- BA
Babayan *et al.*	- Bn
Babayan-Kizner	- BK
Horbowy-Draganik	- HD
Lleonart *et al.*	- Ll
Shepherd	- Sh
Schnute-77(1)	- S71
Schnute-77(2)	- S72
Schnute-77 (process error form)	- S7
Schnute-85	- S8

The second mnemonic reflects the particular form of the surplus production function used :

Beverton-Holt	- B
Fox	- F
Pella-Tomlinson	- PT
Power	- Po
Ricker	- R
Schaefer	- S

and the third mnemonic, the method of parameter estimation. This last mnemonic can itself be divided into three parts, representing the error structure assumed (observation/process - O/P), the assumptions made about the model parameters, and whether or not the cpue data are pre-smoothed (smoothed/unsmoothed - S/U). [Note that ℓn(cpue) minimisation has been used throughout this thesis, so that no distinction for different minimisation criteria is indicated.] As the cpue data have been smoothed only for process error estimators and for procedures based on Gulland's regression method, the last part of the third mnemonic is omitted for all except such cases. The third mnemonic is thus constructed as follows:

1) For Observation error estimators:

a) y_1 = K - OK

b) y_1 Estimated - OE

2) For TLS estimators (observation and process error assumed to have equal variance):

a) $y_1 = K$ - TK

b) y_1 Estimated - TE

3) For Process error estimators:

a) α is Estimated (Smoothed cpue) - PES

b) α is set equal to First cpue value (Smoothed cpue) - PFS

c) α is estimated by the Linear Method (Smoothed cpue) - PLS

d) α is Estimated (Unsmoothed cpue) - PEU

e) α is set equal to First cpue value (Unsmoothed cpue) - PFU

f) α is estimated by the Linear Method (Unsmoothed cpue) - PLU

4) For use with the Gulland procedure:

a) Adaptive Lag 0 method (Unsmoothed cpue) - G0U

b) Adaptive Lag 1 method (Unsmoothed cpue) - G1U

c) ARIMA method (Unsmoothed cpue) - GAU

d) Combined Brown method (Unsmoothed cpue) - GBU

e) EXponential Smoothing method (Unsmoothed cpue) - GXU

f) Linear method (Unsmoothed cpue) - GLU

g) Maximum Entropy method (Unsmoothed cpue) - GMU

h) Adaptive Lag 0 method (Smoothed cpue) - G0S

i) Adaptive Lag 1 method (Smoothed cpue) - G1S

j) ARIMA method (Smoothed cpue) - GAS

k) Combined Brown method (Smoothed cpue) - GBS

l) EXponential Smoothing method (Smoothed cpue) - GXS

m) Linear method (Smoothed cpue) - GLS

n) Maximum Entropy method (Smoothed cpue) - GMS

Table 9.1(a): Estimates of the percentage bias in the estimates of $E_{0.1}$. The standard error of the percentage bias is given in parenthesis.

Operating Model	Estimation Procedure		
	Butterworth - Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Butterworth - Andrew	-0.53 (0.40)+	10.80 (1.84)	14.14 (0.59)
Lleonart *et al.*	-49.56 (0.20)	-2.50 (1.45)+	-29.55 (0.36)
Babayan *et al.*	-20.55 (0.11)	-10.22 (2.04)	-27.55 (2.03)

Note: + not significantly different from zero at the 5% level

Table 9.1(b): Estimates of the percentage bias in the estimates of $Q_{0.1}$. The standard error of the percentage bias is given in parenthesis.

Operating Model	Estimation Procedure		
	Butterworth - Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Butterworth - Andrew	-0.45 (0.63)+	5.69 (1.60)	22.44 (0.94)
Lleonart *et al.*	-46.16 (0.20)	-12.77 (1.24)	-20.82 (0.58)
Babayan *et al.*	-23.87 (0.16)	-5.16 (1.18)	-5.48 (3.95)+

Note: + not significantly different from zero at the 5% level

Table 9.2(a): Estimates of [kurtosis - 3] of the $\hat{E}_{0.1}$ distribution. The value expected if the estimates are normally distributed is zero. The distributions of the estimates corresponding to the entries marked with * are statistically different from the normal distribution at the 5% level, those marked with ** at the 1% level.

Operating Model	Estimation Procedure		
	Butterworth - Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Butterworth - Andrew	-0.098	1.035**	-0.122
Lleonart *et al.*	-0.044	5.806**	0.048
Babayan *et al.*	-0.153	-0.408	5.508**

Table 9.2(b): Estimates of [kurtosis - 3] of the $\hat{Q}_{0.1}$ distribution. The value expected if the estimates are normally distributed is zero. The distributions of the estimates corresponding to the entries marked with * are statistically different from the normal distribution at the 5% level, those marked with ** at the 1% level.

Operating Model	Estimation Procedure		
	Butterworth - Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Butterworth - Andrew	0.138	0.929**	0.067
Lleonart *et al.*	0.165	7.132**	0.276
Babayan *et al.*	0.136	3.778**	2.740**

Table 9.3(a): Estimates of skewness of the $\hat{E}_{0.1}$ distribution, The value expected if the estimates are normally distributed is zero. The distributions of the estimates corresponding to the entries marked with * are statistically different from the normal distribution at the 5% level, those marked with ** at the 1% level.

Operating Model	Estimation Procedure		
	Butterworth - Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Butterworth - Andrew	0.191	-0.268	0.073
Lleonart *et al.*	0.188	1.733**	0.283
Babayan *et al.*	0.039	0.384*	1.180**

Table 9.3(b): Estimates of skewness of the $\hat{Q}_{0.1}$ distribution. The value expected if the estimates are normally distributed is zero. The distributions of the estimates corresponding to the entries marked with * are statistically different from the normal distribution at the 5% level, those marked with ** at the 1% level.

Operating Model	Estimation Procedure		
	Butterworth - Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Butterworth - Andrew	0.142	-0.087	0.296
Lleonart *et al.*	0.170	1.829**	0.468**
Babayan *et al.*	0.059	1.242**	1.326**

Table 9.4: Summary of the first stage of the model selection procedure (Appendices A to C). The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A. Tables (a) to (l) below contain a summary of the results of the three operating model error combinations considered, for the following estimation procedure groups :

Table	Details of estimation procedures used
a	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)
b	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)
c	Babayan-Kizner procedure (Fox and Schaefer forms)
d	Butterworth-Andrew procedure (Fox form)
e	Butterworth-Andrew procedure (Schaefer form)
f	Horbowy-Draganik procedure (Pella-Tomlinson model)
g	Lleonart *et al.* procedure (Fox form)
h	Lleonart *et al.* procedure (Schaefer form)
i	Schnute-77 procedure (based on the Schaefer model)
j	Shepherd procedure
k	Schnute-85 procedure (Fox form)
l	TLS based procedures

9.4(a): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Linear Unsmoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
Brown Unsmoothed cpue data	Accepted for 2nd stage testing	
Maximum Entropy Unsmoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
ARIMA Unsmoothed cpue data	Rejected, s.e. of Q_{MSY} and $Q_{0.1}$ large	A(1),B(1)
Exponential Smoothing Unsmoothed cpue data	Rejected, bias of Q_{MSY} > 40%	A(1),B(1) C(1)
Adaptive (Lag 0) Unsmoothed cpue data	Rejected, bias of Q_{MSY} > 40%	B(1),A(1)
Adaptive (Lag 1) Unsmoothed cpue data	Rejected, bias of Q_{MSY} > 40%	A(1),B(1) C(1)
Linear Smoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
Brown Smoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
Maximum Entropy Smoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
ARIMA Smoothed cpue data	Rejected, s.e. of Q_{MSY} and $Q_{0.1}$ large	A(1)
Exponential Smoothing Smoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
Adaptive (Lag 0) Smoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)
Adaptive (Lag 1) Smoothed cpue data	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(1),B(1) C(1)

9.4(b): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Linear Unsmoothed cpue data	Rejected, bias of $Q_{0.1}$ > 40%	A(2)
Brown Unsmoothed cpue data	Accepted for 2nd stage testing	
Maximum Entropy Unsmoothed cpue data	Rejected, bias of $Q_{0.1}$ and Q_{MSY} larger than Brown method	A(2),B(2)
ARIMA Unsmoothed cpue data	Rejected, s.e. of Q_{MSY} and $Q_{0.1}$ large	A(2),B(2)
Exponential Smoothing Unsmoothed cpue data	Rejected, bias of $Q_{0.1}$ and Q_{MSY} larger than Brown method	A(2),B(2)
Adaptive (Lag 0) Unsmoothed cpue data	Rejected, bias of $Q_{0.1}$ and Q_{MSY} larger than Brown method	A(2),B(2)
Adaptive (Lag 1) Unsmoothed cpue data	Rejected, bias of $Q_{0.1}$ and Q_{MSY} larger than Brown method	A(2),B(2)
Linear Smoothed cpue data	Rejected, bias of $E_{0.1}$ greater than corresponding unsmoothed procedure	A(2),B(2) C(2)
Brown Smoothed cpue data	Rejected, bias of $E_{0.1}$ greater than corresponding unsmoothed procedure	A(2),B(2) C(2)
Maximum Entropy Smoothed cpue data	Rejected, bias of $E_{0.1}$ greater than corresponding unsmoothed procedure	A(2),B(2) C(2)
ARIMA Smoothed cpue data	Rejected, s.e. of Q_{MSY} and $Q_{0.1}$ large	A(2)
Exponential Smoothing Smoothed cpue data	Rejected, bias of $E_{0.1}$ greater than corresponding unsmoothed procedure	A(2),B(2) C(2)
Adaptive (Lag 0) Smoothed cpue data	Rejected, bias of $E_{0.1}$ greater than corresponding unsmoothed procedure	A(2),B(2) C(2)
Adaptive (Lag 1) Smoothed cpue data	Rejected, bias of $E_{0.1}$ greater than corresponding unsmoothed procedure	A(2),B(2) C(2)

9.4(c): Babayan-Kizner procedure (Fox and Schaefer forms)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Unsmoothed cpue data q estimated (Fox)	Rejected, bias > 40% for all quantities	B(3),C(3)
Unsmoothed cpue data $(C/E)_1 = qK$ (Fox)	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(3),B(3) C(3)
Unsmoothed cpue data Linear method (Fox)	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(3),B(3) C(3)
Smoothed cpue data q estimated (Fox)	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(3),B(3) C(3)
Smoothed cpue data $(C/E)_1 = qK$ (Fox)	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(3),B(3) C(3)
Smoothed cpue data Linear method (Fox)	Accepted for 2nd stage testing	
Unsmoothed cpue data q estimated (Sch.)	Rejected, bias > 40% for all quantities	A(3)
Unsmoothed cpue data $(C/E)_1 = qK$ (Sch.)	Accepted for 2nd stage testing	
Unsmoothed cpue data Linear method (Sch.)	Rejected, bias in general larger than Linear method	A(3),B(3) C(3)
Smoothed cpue data q estimated (Sch.)	Rejected, bias in general larger than Linear method	A(3),B(3) C(3)
Smoothed cpue data $(C/E)_1 = qK$ (Sch.)	Rejected, bias in general larger than Linear method	A(3),B(3) C(3)
Smoothed cpue data Linear method (Sch.)	Rejected, bias in general larger than Linear method	A(3),B(3) C(3)

9.4(e): Butterworth-Andrew procedure (Schaefer form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error $y_1 = K$	Accepted for 2nd stage testing	
Observation Error y_1 estimated	Rejected, s.e. of all quantities large	C(5)
Process Error Model Unsmoothed cpue data q estimated	Rejected, bias > 40% for all quantities	A(5),B(5)
Process Error Model Unsmoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Unsmoothed cpue data Linear method	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Smoothed cpue data q estimated	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Smoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Smoothed cpue data Linear method	Accepted for 2nd stage testing	

9.4(f): Horbowy-Draganik procedure (Pella-Tomlinson model)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error $y_1 = K$	Rejected, bias > 40% for all quantities	C(6)
Observation Error y_1 estimated	Rejected, bias > 40% for all quantities	C(6)
Process Error Model Unsmoothed cpue data q estimated	Rejected, bias > 40% for all quantities	A(6),B(6) C(6)
Process Error Model Unsmoothed cpue data $(C/E)_1 = qK$	Rejected, bias of Q_{MSY} > 40%	A(6),B(6)
Process Error Model Unsmoothed cpue data Linear method	Rejected, bias of Q_{MSY} > 40%	A(6),B(6) C(6)
Process Error Model Smoothed cpue data q estimated	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(6),B(6) C(6)
Process Error Model Smoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Smoothed cpue data Linear method	Accepted for 2nd stage testing	

9.4(g): Lleonart *et al.* procedure (Fox form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error $\hat{y}_1 = K$	Rejected, bias > 40% for all quantities	C(7)
Observation Error y_1 estimated	Rejected, bias of E_{MSY}, MSY, Q_{MSY} and $E_{0.1}$ > 40%	C(7)
Process Error Model Unsmoothed cpue data q estimated	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	A(7),B(7)
Process Error Model Unsmoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Unsmoothed cpue data Linear method	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Smoothed cpue data q estimated	Rejected, bias of E_{MSY} > 40%	B(7),C(7)
Process Error Model Smoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than Linear method (smoothed data)	
Process Error Model Smoothed cpue data Linear method	Accepted for 2nd stage testing	

9.4(h): Lleonart *et al.* procedure (Schaefer form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error $y_1 = K$	Rejected, bias of E_{MSY} and $E_{0.1}$ > 40%	C(8)
Observation Error y_1 estimated	Rejected, bias > 40% for all quantities	A(8),B(8) C(8)
Process Error Model Unsmoothed cpue data q estimated	Rejected, bias of $E_{0.1}$ > 40%	A(8),B(8)
Process Error Model Unsmoothed cpue data $(C/E)_1 = qK$	Accepted for 2nd stage testing	
Process Error Model Unsmoothed cpue data Linear method	Rejected, bias in general larger than $(C/E)_1 = qK$ (unsmoothed data)	
Process Error Model Smoothed cpue data q estimated	Rejected, bias in general larger than $(C/E)_1 = qK$ (unsmoothed data)	
Process Error Model Smoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than $(C/E)_1 = qK$ (unsmoothed data)	
Process Error Model Smoothed cpue data Linear method	Rejected, bias in general larger than $(C/E)_1 = qK$ (unsmoothed data)	

9.4(i): Schnute-77 procedure (based on the Schaefer form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error (1) $y_1 = K$	Accepted for 2nd stage testing	
Observation Error (1) y_1 estimated	Rejected, s.e.'s for all quantities large	
Observation Error (2) $y_1 = K$	Accepted for 2nd stage testing	
Observation Error (2) y_1 estimated	Rejected, bias in general larger than $(y_1 = K)$	
Process Error Model Unsmoothed cpue data q estimated	Rejected, bias of $Q_{0.1} > 40\%$	A(9)
Process Error Model Unsmoothed cpue data $(C/E)_1 = qK$	Rejected, bias in general larger than $(C/E)_1 = qK$ (smoothed data)	
Process Error Model Unsmoothed cpue data Linear method	Rejected, bias in general larger than $(C/E)_1 = qK$ (smoothed data)	
Process Error Model Smoothed cpue data q estimated	Rejected, bias in general larger than $(C/E)_1 = qK$ (smoothed data)	
Process Error Model Smoothed cpue data $(C/E)_1 = qK$	Accepted for 2nd stage testing	
Process Error Model Smoothed cpue data Linear method	Rejected, bias in general larger than $(C/E)_1 = qK$ (smoothed data)	

9.4(j): Shepherd procedure

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error $y_1 = K$	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	C(10)
Observation Error y_1 estimated	Rejected, bias > 40% for all quantities	A(10) B(10)
Process Error Model Unsmoothed cpue data q estimated	Rejected, bias > 40% for all quantities	A(10) B(10)
Process Error Model Unsmoothed cpue data $(C/E)_1 = qK$	Rejected, bias > 40% for all quantities	A(10) C(10)
Process Error Model Unsmoothed cpue data Linear method	Rejected, the procedure was unable to converge for all data sets	A(10) B(10)
Process Error Model Smoothed cpue data q estimated	Rejected, bias > 40% for all quantities	A(10) B(10)
Process Error Model Smoothed cpue data $(C/E)_1 = qK$	Rejected, bias of Q_{MSY} > 40%	B(10) C(10)
Process Error Model Smoothed cpue data Linear method	Rejected, the procedure was unable to converge for all data sets	A(10) B(10)

9.4(k): Schnute-85 procedure (Fox form)

Estimation Procedure	Result of 1st stage testing	Table Ref.
Observation Error $y_1 = K$	Accepted for 2nd stage testing	
Observation Error y_1 estimated	Rejected, bias of E_{MSY}, Q_{MSY}, $E_{0.1}$ and $Q_{0.1}$ > 40%	A(11) B(11) C(11)

9.4(l): TLS based procedures

Estimation Procedure	Result of 1st stage testing	Table Ref.
Butterworth-Andrew Schaefer form $y_1 = K$	Accepted for 2nd stage testing	
Butterworth-Andrew Schaefer form y_1 estimated	Rejected, bias in general larger than Schaefer form ($y_1 = K$)	
Butterworth-Andrew Fox form $y_1 = K$	Rejected, bias in general larger than Schaefer form ($y_1 = K$)	
Butterworth-Andrew Fox form y_1 estimated	Rejected, bias of Q_{MSY} and $Q_{0.1}$ > 40%	B(12) C(12)
Ricker Model	Rejected, bias in general larger than Schaefer form ($y_1 = K$)	
Power Model	Rejected, bias > 40% for all quantities	

Table 9.5: Estimation procedures selected for further investigation, after consideration of the biases reported in Appendices A to C (see text for the model-selection algorithm used and Table 9.4 for its application). The acronym (see Appendix 9.A) assigned to each procedure is used again in the robustness tests summary tables (Appendix D).

Acronym	Estimation Procedure
Bn-F-GBU	Babayan *et al.* Brown (unsmoothed cpue data) Fox form
Bn-S-GBU	Babayan *et al.* Brown (unsmoothed cpue data) Schaefer form
BK-F-PLS	Babayan and Kizner Linear Method (smoothed cpue data) Fox form
BK-S-PFU	Babayan and Kizner $(C/E)_1 = qK$ (unsmoothed cpue data) Schaefer form
BA-F-OK	Butterworth-Andrew Observation Error Model ($y_1 = K$) Fox form
BA-S-OK	Butterworth-Andrew Observation Error Model ($y_1 = K$) Schaefer form
BA-F-PLS	Butterworth-Andrew Process Error Model Linear Method (smoothed cpue data) Fox form
BA-S-PLS	Butterworth-Andrew Process Error Model Linear Method (smoothed cpue data) Schaefer form
HD-PT-PLS	Horbowy-Draganik Process Error Model Linear Method (smoothed cpue data) Pella-Tomlinson form
Ll-F-PLS	Lleonart *et al.* Process Error Model Linear Method (smoothed cpue data) Fox form
Ll-S-PFU	Lleonart *et al.* Process Error Model $(C/E)_1 = qK$ (unsmoothed cpue data) Schaefer form
S71-S-OK	Schnute-77(1) Observation Error Model ($y_1 = K$)
S72-S-OK	Schnute-77(2) Observation Error Model ($y_1 = K$)
S7-S-PFS	Schnute-77 Process Error Model $(C/E)_1 = qK$ (smoothed cpue data)
S8-F-OK	Schnute-85 Observation Error Model ($y_1 = K$) Fox form
BA-S-TK	Butterworth-Andrew ($y_1 = K$) Schaefer form TLS Method

Table 9.6: Summary of the second stage of the model selection procedure (Appendices D and E). The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A and the variants of this operating model used here are given in Table 7.2. Tables (a) to (e) below contain a summary of the biases (Appendix D) and Table (f) a summary of the discrepancies (Appendix E). Table (g) contains a summary of the average ranks reported in Tables (a) to (f). The statistics reported in Tables (a) to (e) for estimation procedure E and management variable V are :

Average bias : The average bias (in %) of V using estimation procedure E over the 17 robustness tests.

Average rank : For each robustness test, the estimated biases of V are ordered from lowest to highest and a rank of 1 is assigned to the lowest, 2 to the next lowest, etc. The average rank assigned to estimation procedure E is then computed.

Ranks < 5 : The number of times the rank assigned to estimation procedure E for management variable V is below 5.

Ranks > 12 : The number of times the rank assigned to estimation procedure E for management variable V is above 12.

Maximum bias : The largest estimated bias (in %) for V in the 17 robustness tests performed, when estimation procedure E is used.

The results in Table (f) are obtained in the same way, using the discrepancies of $Q_{0.1}$ instead of the biases in the computations.

9.6(a): Summary of the estimated biases of the estimates of E_{MSY} given in Appendix D.

Estimation Procedure	Average Bias (%)	S.e. of Average Bias (%)	Average Rank	#Ranks < 5	#Ranks > 12	Maximum Absolute Bias (%)
Bn-F-GBU	44.52	0.49	14.88	1	15	73.43
Bn-S-GBU	9.00	0.22	5.18	9	1	28.15
BK-F-PLS	17.40	0.40	9.82	1	1	38.62
BK-S-PSU	-11.94	0.13	7.65	2	1	36.36
BA-F-OK	27.27	0.37	13.94	1	16	49.71
BA-S-OK *	-11.94	0.22	6.53	4	0	34.77
BA-F-PLS	22.73	0.42	12.94	1	12	44.69
BA-S-PLS	-17.17	0.25	11.00	1	4	38.49
HD-PT-PLS	20.39	0.40	11.59	1	11	41.97
L1-F-PLS *	6.34	0.37	5.65	8	1	26.64
L1-S-PFU	-4.31	0.25	3.41	14	0	31.27
S71-S-OK *	-9.34	0.22	4.06	11	0	32.84
S72-S-OK *	-11.49	0.21	5.71	4	1	35.96
S7-S-PFS *	-13.05	0.21	7.47	2	0	34.27
S8-F-OK	7.74	0.19	7.24	7	3	38.70
BA-S-TK *	-14.26	0.19	8.94	1	2	36.44

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

9.6(b): Summary of the estimated biases of the estimates of MSY given in Appendix D.

Estimation Procedure	Average Bias (%)	S.e. of Average Bias (%)	Average Rank	#Ranks < 5	#Ranks > 12	Maximum Absolute Bias (%)
Bn-F-GBU	33.75	0.31	15.76	0	17	50.23
Bn-S-GBU	28.20	0.20	14.94	0	17	50.94
BK-F-PLS	11.66	0.30	8.47	2	0	24.04
BK-S-PFU	10.44	0.73	7.88	1	1	31.01
BA-F-OK	15.19	0.32	11.24	0	2	31.44
BA-S-OK *	8.39	0.51	5.29	8	1	19.81
BA-F-PLS	16.64	0.32	12.35	0	10	28.94
BA-S-PLS	7.21	0.26	3.76	13	0	13.45
HD-PT-PLS	14.81	0.31	10.65	0	0	27.18
L1-F-PLS *	2.63	0.28	2.53	14	0	17.46
L1-S-PFU	15.53	0.24	12.82	1	14	33.70
S71-S-OK *	9.44	0.24	7.82	0	0	18.84
S72-S-OK *	7.33	0.22	3.76	14	0	16.38
S7-S-PFS *	8.38	0.21	5.76	3	0	17.44
S8-F-OK	-6.74	0.03	7.06	8	5	19.32
BA-S-TK *	8.25	0.20	5.88	3	1	19.02

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

9.6(c): Summary of the estimated biases of the estimates of Q_{MSY} given in Appendix D.

Estimation Procedure	Average Bias (%)	S.e. of Average Bias (%)	Average Rank	#Ranks < 5	#Ranks > 12	Maximum Absolute Bias (%)
Bn-F-GBU	34.46	0.71	12.76	1	13	62.16
Bn-S-GBU	1.08	0.44	4.47	10	0	23.02
BK-F-PLS	86.20	0.71	15.94	0	17	116.80
BK-S-PFU	-12.49	0.84	8.82	1	1	36.74
BA-F-OK	36.48	0.53	13.71	1	15	62.97
BA-S-OK *	-3.17	0.33	4.00	12	0	25.81
BA-F-PLS	30.80	0.53	12.29	1	12	51.96
BA-S-PLS	-11.51	0.33	7.82	1	1	32.47
HD-PT-PLS	28.16	0.51	11.24	1	2	49.00
L1-F-PLS *	3.58	0.36	6.35	4	1	27.80
L1-S-PFU	-21.43	0.21	11.41	0	5	41.85
S71-S-OK *	-0.29	0.32	3.65	12	0	23.52
S72-S-OK *	-3.04	0.30	3.53	14	0	29.59
S7-S-PFS *	-7.00	0.29	5.18	5	0	25.37
S8-F-OK	0.11	0.33	8.41	2	1	39.33
BA-S-TK *	-9.22	0.26	6.41	3	0	30.79

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

9.6(d): Summary of the estimated biases of the estimates of $E_{0.1}$ given in Appendix D.

Estimation Procedure	Average Bias (%)	S.e. of Average Bias (%)	Average Rank	#Ranks < 5	#Ranks > 12	Maximum Absolute Bias (%)
Bn-F-GBU	38.19	0.47	15.71	0	16	55.74
Bn-S-GBU	20.58	0.25	12.94	0	12	32.53
BK-F-PLS	12.71	0.37	10.35	1	2	25.98
BK-S-PFU	-3.06	0.68	6.88	5	2	17.15
BA-F-OK	21.13	0.39	13.47	1	16	40.13
BA-S-OK *	-2.62	0.24	5.18	6	0	13.76
BA-F-PLS	17.83	0.40	12.35	1	11	31.12
BA-S-PLS	-8.40	0.27	9.35	2	1	18.69
HD-PT-PLS	2.96	0.34	5.18	9	0	14.89
L1-F-PLS *	2.76	0.35	6.65	7	0	19.41
L1-S-PFU	8.21	0.29	5.94	7	1	17.10
S71-S-OK *	0.27	0.23	3.82	10	0	11.21
S72-S-OK *	-2.13	0.23	4.65	9	0	15.34
S7-S-PFS *	-3.82	0.23	6.00	4	0	13.11
S8-F-OK	2.39	0.19	10.00	2	6	34.90
BA-S-TK *	-5.18	0.21	7.53	4	1	15.97

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

9.6(e): Summary of the estimated biases of the estimates of $Q_{0.1}$ given in Appendix D.

Estimation Procedure		Average Bias (%)	S.e. of Average Bias (%)	Average Rank	#Ranks < 5	#Ranks > 12	Maximum Absolute Bias (%)
Bn-F-GBU		26.45	0.67	12.65	1	12	52.51
Bn-S-GBU		9.96	0.47	8.35	2	0	27.74
BK-F-PLS		75.86	0.67	16.00	0	17	92.70
BK-S-PFU		-6.75	0.91	8.18	2	1	19.70
BA-F-OK		28.88	0.50	14.00	0	16	53.55
BA-S-OK	*	5.36	0.34	4.82	7	0	14.62
BA-F-PLS		23.51	0.50	12.12	0	8	39.37
BA-S-PLS		-3.75	0.35	5.29	8	1	13.97
HD-PT-PLS		7.25	0.42	7.53	2	0	22.06
L1-F-PLS	*	1.64	0.36	5.41	10	1	21.80
L1-S-PFU		-18.44	0.28	11.29	1	7	30.01
S71-S-OK	*	8.49	0.35	7.76	3	0	17.98
S72-S-OK	*	-0.02	0.33	5.88	5	0	15.00
S7-S-PFS	*	1.02	0.31	3.52	12	0	9.17
S8-F-OK		-3.93	0.27	9.18	4	5	33.30
BA-S-TK	*	-1.25	0.29	4.00	11	0	11.84

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

9.6(f): Summary of the estimated expected discrepancies (EED) of the estimates of $Q_{0.1}$ given in Appendix E.

Estimation Procedure	Average EED (%)	S.e. of Average EED (%)	Average Rank	#Ranks < 5	#Ranks > 12	Maximum Absolute EED (%)
Bn-F-GBU	38.43	0.56	14.65	0	17	58.58
Bn-S-GBU	24.63	0.35	11.65	0	1	37.56
BK-F-PLS	73.95	0.63	15.59	0	16	93.16
BK-S-PFU	23.00	0.87	8.76	1	2	71.41
BA-F-OK	32.53	0.44	13.24	0	14	57.40
BA-S-OK *	17.34	0.24	5.00	9	1	26.65
BA-F-PLS	28.54	0.41	12.06	0	10	46.03
BA-S-PLS	18.22	0.25	6.29	4	1	30.14
HD-PT-PLS	20.72	0.32	9.18	0	0	32.87
L1-F-PLS *	17.98	0.25	6.82	2	0	26.89
L1-S-PFU	21.57	0.18	9.41	3	2	31.86
S71-S-OK *	18.01	0.25	6.76	2	0	27.47
S72-S-OK *	16.63	0.23	5.12	9	0	24.36
S7-S-PFS *	15.11	0.22	2.76	16	0	22.95
S8-F-OK	19.58	0.24	6.88	7	4	33.98
BA-S-TK *	14.34	0.19	1.88	15	0	20.71

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

9.6(g): Summary of the average ranks of the biases reported in Tables 9.6(a) to (e) (Columns 2 to 6) and of the discrepancies in Table 9.6(f) (Column 8).

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$	Average rank	$Q_{0.1}$
Bn-F-GBU	14.88	15.76	12.76	15.71	12.65	14.35	14.65
Bn-S-GBU	5.18	14.94	4.47	12.94	8.35	9.18	11.65
BK-F-PLS	9.82	8.47	15.94	10.35	16.00	12.12	15.59
BK-S-PFU	7.65	7.88	8.82	6.88	8.18	7.88	8.76
BA-F-OK	13.94	11.24	13.71	13.47	14.00	13.27	13.24
BA-S-OK *	6.53	5.29	4.00	5.18	4.82	5.16	5.00
BA-F-PLS	12.94	12.35	12.29	12.35	12.12	12.41	12.06
BA-S-PLS	11.00	3.76	7.82	9.35	5.29	7.44	6.29
HD-PT-PLS	11.59	10.65	11.24	5.18	7.53	9.24	9.18
L1-F-PLS *	5.65	$\boxed{2.53}$	6.35	6.65	5.41	5.32	6.82
L1-S-PFU	$\boxed{3.41}$	12.82	11.41	5.94	11.29	8.97	9.41
S71-S-OK *	4.06	7.82	3.65	$\boxed{3.82}$	7.76	5.42	6.76
S72-S-OK *	5.71	3.76	$\boxed{3.53}$	4.65	5.88	$\boxed{4.71}$	5.12
S7-S-PFS *	7.47	5.76	5.18	6.00	$\boxed{3.52}$	5.59	2.76
S8-F-OK	7.24	7.06	8.41	10.00	9.18	8.38	6.88
BA-S-TK *	8.94	5.88	6.41	7.53	4.00	6.55	$\boxed{1.88}$

Note: * one of the six selected estimation procedures
best in its category
second best in its category
worst in its category

Table 9.7: Summary of the estimates of percentage expected discrepancy for the best estimators of $Q_{0.1}$ for various robustness tests. The standard error of the estimated percentage expected discrepancy is given in parenthesis.

Robustness Test	Butterworth-Andrew (Schaefer form) Observation error $y_1 = K$ (BA-S-OK)	Lleonart *et al.* (Fox form) Process error Smoothed cpue (L1-F-PLS)	Schnute-77(1) (Schaefer form) Observation error $y_1 = K$ (S71-S-OK)
σ_r=0.2, σ_q=0.1	13.39 (0.72)	15.34 (0.79)	15.64 (0.87)
σ_r=0.0, σ_q=0.13	9.87 (0.56)	14.72 (0.80)	11.00 (0.59)
σ_r=0.3, σ_q=0.0	21.36 (1.38)	18.94 (1.10)	22.56 (1.39)
σ_r=0.2, σ_q=0.2	20.23 (1.19)	26.81 (1.92)	22.85 (1.32)
M = 0.2	13.76 (0.76)	13.50 (0.64)	16.20 (0.85)
M = 0.4	16.35 (0.96)	18.21 (0.99)	17.09 (0.98)
M = 0.5	19.18 (1.18)	21.89 (1.25)	19.71 (1.19)
a_m = 3	15.12 (0.86)	15.59 (0.81)	16.64 (0.91)
a_m = 5	13.66 (0.79)	15.04 (0.75)	14.72 (0.83)
a_r = 4	25.68 (1.50)	26.89 (1.66)	27.47 (1.60)
δ = 1.0	12.73 (0.72)	14.99 (0.74)	13.31 (0.75)
δ = 0.25	15.35 (0.87)	15.49 (0.80)	16.93 (0.93)
MSY = 200	19.41 (1.05)	14.86 (0.86)	22.66 (1.16)
MSY = 300	13.19 (0.67)	15.97 (0.79)	13.37 (0.68)
B^e_{MSY}/K^e = 0.3	26.65 (0.72)	16.42 (0.67)	13.50 (0.73)
B^e_{MSY}/K^e = 0.45	19.38 (1.07)	19.46 (1.13)	21.51 (1.11)
$y_1 \neq K$	19.46 (1.32)	20.78 (1.43)	21.01 (1.32)

Note: best in its category
second best in its category
worst in its category

Table 9.7 Continued

Robustness Test	Butterworth-Andrew (Schaefer form) TLS Method $y_1 = K$ (BA-S-TK)	Schnute-77(2) (Schaefer form) Observation error $y_1 = K$ (S72-S-OK)	Schnute-77 (Schaefer form) Process Error Smoothed cpue $(C/E)_1 = qK$ (S7-S-PFS)
$\sigma_r=0.2,\ \sigma_q=0.1$	12.10 (0.65)	14.60 (0.83)	12.58 (0.66)
$\sigma_r=0.0,\ \sigma_q=0.13$	12.64 (0.61)	10.08 (0.57)	12.63 (0.69)
$\sigma_r=0.3,\ \sigma_q=0.0$	14.98 (0.88)	20.92 (1.19)	16.71 (0.96)
$\sigma_r=0.2,\ \sigma_q=0.2$	20.71 (1.22)	20.32 (1.16)	22.95 (1.55)
M = 0.2	10.58 (0.57)	14.21 (0.78)	11.22 (0.61)
M = 0.4	14.33 (0.76)	16.12 (0.95)	14.81 (0.82)
M = 0.5	16.79 (0.91)	18.76 (1.14)	17.53 (0.99)
$a_m = 3$	12.21 (0.66)	15.22 (0.87)	12.90 (0.71)
$a_m = 5$	12.13 (0.63)	13.86 (0.79)	12.52 (0.68)
$a_r = 4$	19.36 (1.13)	24.36 (1.41)	20.91 (1.26)
$\delta = 1.0$	12.18 (0.61)	13.12 (0.73)	12.33 (0.65)
$\delta = 0.25$	12.25 (0.66)	15.86 (0.88)	12.94 (0.72)
MSY = 200	14.10 (0.76)	19.81 (1.09)	14.95 (0.81)
MSY = 300	13.06 (0.60)	13.33 (0.66)	13.17 (0.67)
$B^e_{MSY}/K^e = 0.3$	15.14 (0.62)	13.60 (0.72)	14.46 (0.65)
$B^e_{MSY}/K^e = 0.45$	14.55 (0.83)	19.64 (1.07)	16.07 (0.93)
$y_1 \neq K$	16.71 (1.09)	18.89 (1.09)	18.22 (1.13)

Note: best in its category
second best in its category
worst in its category

Table 9.8: Summary (developed as for Table 9.7) of the estimates of percentage expected discrepancy for the best estimators of $Q_{0.1}$ for various robustness tests when the number of simulations is increased to 500. The standard error of the estimated percentage expected discrepancy is given in parenthesis.

Robustness Test	Butterworth-Andrew (Schaefer form) Observation error $y_1 = K$ (BA-S-OK)	Lleonart *et al.* (Fox form) Process error Smoothed cpue (L1-F-PLS)	Schnute-77(1) (Schaefer form) Observation error $y_1 = K$ (S71-S-OK)
$\sigma_r=0.2$, $\sigma_q=0.1$	14.93 (0.58)	16.80 (0.63)	16.34 (0.62)
$\sigma_r=0.0$, $\sigma_q=0.13$	10.29 (0.38)	15.45 (0.58)	11.55 (0.42)
$\sigma_r=0.3$, $\sigma_q=0.0$	21.51 (0.90)	19.96 (0.88)	22.91 (0.93)
$\sigma_r=0.2$, $\sigma_q=0.2$	21.04 (0.82)	29.04 (1.43)	23.97 (0.94)
M = 0.2	14.56 (0.55)	14.67 (0.48)	17.21 (0.61)
M = 0.4	16.89 (0.68)	20.10 (0.83)	17.78 (0.71)
M = 0.5	19.89 (0.85)	24.34 (1.07)	20.56 (0.86)
$a_m = 3$	15.77 (0.61)	17.08 (0.65)	17.43 (0.66)
$a_m = 5$	14.18 (0.55)	16.45 (0.59)	15.35 (0.59)
$a_r = 4$	26.09 (1.07)	48.54 (1.78)	27.79 (1.13)
$\delta = 1.0$	13.23 (0.50)	16.42 (0.58)	13.91 (0.53)
$\delta = 0.25$	16.03 (0.62)	16.99 (0.64)	17.78 (0.67)
MSY = 200	20.85 (0.76)	16.50 (0.69)	24.28 (0.84)
MSY = 300	12.96 (0.45)	17.20 (0.61)	13.16 (0.47)
$B^e_{MSY}/K^e = 0.3$	13.82 (0.48)	17.24 (0.50)	13.93 (0.50)
$B^e_{MSY}/K^e = 0.45$	20.11 (0.76)	21.06 (0.90)	22.29 (0.80)
$y_1 \neq K$	17.98 (0.81)	20.43 (0.94)	19.25 (0.83)

Table 9.9: Summary (developed as for Table 9.7) of the estimates of percentage expected discrepancy for the best estimators of $Q_{0.1}$ for various robustness tests when the number of simulations is increased to 1000. The standard error of the estimated percentage expected discrepancy is given in parenthesis.

Robustness Test	Butterworth-Andrew (Schaefer form) Observation error $y_1 = K$ (BA-S-OK)	Lleonart *et al.* (Fox form) Process error Smoothed cpue (L1-F-PLS)	Schnute-77(1) (Schaefer form) Observation error $y_1 = K$ (S71-S-OK)
σ_r=0.2, σ_q=0.1	14.84 (0.41)	17.10 (0.48)	16.28 (0.44)
σ_r=0.0, σ_q=0.13	10.03 (0.26)	15.65 (0.40)	11.24 (0.28)
σ_r=0.3, σ_q=0.0	21.60 (0.66)	19.79 (0.64)	22.89 (0.67)
σ_r=0.2, σ_q=0.2	20.89 (0.59)	29.88 (1.06)	24.05 (0.67)
M = 0.2	14.40 (3.80)	14.67 (0.36)	16.97 (0.43)
M = 0.4	17.02 (0.49)	20.73 (0.64)	17.89 (0.50)
M = 0.5	17.80 (0.89)	25.27 (0.84)	20.90 (0.62)
a_m = 3	15.68 (0.43)	17.41 (0.49)	17.36 (0.46)
a_m = 5	14.09 (0.39)	16.72 (0.45)	15.30 (0.41)
a_r = 4	25.82 (0.76)	29.87 (0.99)	27.19 (0.77)
δ = 1.0	13.26 (0.35)	16.61 (0.44)	13.94 (0.37)
δ = 0.25	15.93 (0.44)	17.38 (0.49)	17.66 (0.47)
MSY = 200	20.67 (0.54)	17.07 (0.52)	23.86 (0.59)
MSY = 300	13.77 (0.42)	17.23 (0.46)	13.13 (0.33)
B^e_{MSY}/K^e = 0.3	13.96 (0.35)	17.40 (0.39)	14.10 (0.36)
B^e_{MSY}/K^e = 0.45	19.84 (0.53)	21.41 (0.67)	21.99 (0.56)
$y_1 \neq K$	16.97 (0.50)	20.73 (0.63)	18.11 (0.52)

Table 9.10: Estimates of the percentage bias in the estimates of the parameters and variables used in the management of ICSEAF hake stocks for selected estimation procedures listed in Table 9.5. The standard error of each bias estimate (expressed as a percentage) is given in parenthesis. Column 1 contains the acronym for each procedure. The following data series are used:

Table	Years of cpue data used in the simulations
a	1965 - 1979
b	1965 - 1981
c	1965 - 1982
d	1965 - 1983
e	1965 - 1984

9.10(a): Data from 1965 to 1979

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	-56.57 (3.85)	-59.49 (3.59)	-56.57 (3.92)	-58.48 (3.68)	-59.15 (3.69)
BA-S-OK	-32.38 (2.72)	-14.48 (3.46)	-32.04 (2.84)	-25.54 (3.00)	-26.38 (3.07)
BA-S-PLS	-42.08 (2.82)	-26.98 (3.48)	-39.51 (3.08)	-36.23 (3.10)	-34.48 (3.34)
L1-F-PLS	-5.16 (2.96)+	-11.71 (2.60)	-10.60 (2.84)	-9.33 (2.83)	-12.37 (2.78)
S71-S-OK	-4.99 (1.12)	17.66 (1.40)	-2.81 (1.48)	4.62 (1.24)	5.28 (1.60)
S72-S-OK	-6.22 (1.02)	16.46 (1.25)	-5.25 (1.36)	3.26 (1.12)	2.63 (1.47)+
S7-S-PFS	-8.00 (1.08)	12.34 (1.20)	-7.59 (1.37)	1.29 (1.20)+	0.10 (1.49)+
S8-F-OK	-6.74 (1.00)	18.41 (1.30)	-6.38 (1.32)	2.68 (1.10)	1.41 (1.43)

Note: + not significantly different from zero at the 5% level

9.10(b): Data from 1965 to 1981

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	-12.68 (3.81)	-19.84 (3.46)	-12.05 (3.96)	-16.52 (3.65)	-17.29 (3.72)
BA-S-OK	-21.19 (2.05)	-2.47 (2.51)+	-19.24 (1.91)	-13.23 (2.26)	-12.53 (2.41)
BA-S-PLS	-15.53 (1.08)	8.16 (1.25)	-11.21 (1.40)	-6.99 (1.19)	-3.84 (1.52)
L1-F-PLS	-0.73 (1.61)+	-6.64 (1.36)	-8.77 (1.55)	-5.09 (1.54)	-11.52 (1.51)
S71-S-OK	-8.63 (0.95)	11.26 (1.08)	-5.75 (0.82)	0.60 (1.04)+	2.07 (0.87)
S72-S-OK	-9.45 (0.85)	15.13 (0.67)	-6.71 (1.18)	-0.30 (0.94)+	16.10 (0.77)
S7-S-PFS	-12.90 (0.90)	7.15 (1.01)	-12.59 (1.12)	-4.10 (1.00)	-5.33 (1.21)
S8-F-OK	-11.63 (0.84)	11.15 (1.01)	-10.71 (1.10)	-2.70 (0.93)	-3.30 (1.19)

Note: + not significantly different from zero at the 5% level

9.10(c): Data from 1965 to 1982

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	26.27 (1.76)	15.57 (1.47)	33.30 (2.31)	20.72 (1.68)	25.35 (2.18)
BA-S-OK	-10.30 (0.94)	10.60 (1.06)	-3.69 (1.35)	-1.23 (1.03)+	4.31 (1.46)
BA-S-PLS	-15.75 (1.29)	8.33 (1.43)	-10.82 (1.59)	-7.24 (1.42)	-3.41 (1.72)
L1-F-PLS	4.26 (1.83)	-1.56 (1.47)+	-0.29 (1.33)+	-0.32 (1.75)+	-3.36 (1.72)+
S71-S-OK	-8.18 (0.98)	11.34 (1.09)	-1.19 (1.40)+	1.10 (1.07)+	7.02 (1.52)
S72-S-OK	-9.93 (0.82)	9.52 (0.89)	15.00 (0.76)	-0.83 (0.90)+	4.69 (1.30)
S7-S-PFS	-11.98 (1.03)	8.63 (1.08)	-8.19 (1.30)	-3.09 (1.13)	-0.57 (1.41)+
S8-F-OK	-11.99 (0.97)	10.60 (1.08)	-7.58 (1.26)	-3.09 (1.06)	0.09 (1.37)+

Note: + not significantly different from zero at the 5% level

9.10(d): Data from 1965 to 1983

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	25.53 (1.44)	14.36 (1.13)	34.95 (1.88)	20.02 (1.38)	26.91 (1.77)
BA-S-OK	-10.81 (0.74)	9.20 (0.79)	-2.18 (1.13)+	-1.80 (0.82)	5.95 (1.22)
BA-S-PLS	-15.37 (0.95)	8.66 (0.99)	-8.79 (1.31)	-6.81 (1.04)	-1.21 (1.42)+
L1-F-PLS	6.16 (1.51)	0.06 (1.14)+	4.87 (1.58)	1.50 (1.44)+	1.65 (1.04)+
S71-S-OK	-8.67 (0.78)	10.07 (0.82)	0.26 (1.17)+	0.56 (0.86)+	8.58 (1.27)
S72-S-OK	-10.21 (0.75)	8.50 (0.79)	-1.61 (1.14)	-1.13 (0.83)	6.56 (1.23)
S7-S-PFS	-11.65 (0.84)	8.90 (0.82)	-5.62 (1.17)	-2.72 (0.93)	2.22 (5.41)+
S8-F-OK	-12.57 (0.71)	9.61 (0.74)	-6.35 (1.04)	-3.74 (0.78)	1.43 (1.13)+

Note: + not significantly different from zero at the 5% level

9.10(e): Data from 1965 to 1984

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	26.13 (1.35)	14.42 (1.02)	37.72 (1.68)	20.59 (1.30)	29.53 (1.69)
BA-S-OK	-10.69 (0.75)	8.60 (0.75)	-0.51 (1.11)+	-1.67 (0.83)	7.76 (1.21)
BA-S-PLS	-15.00 (1.01)	8.23 (1.01)	-8.51 (1.35)	-6.41 (1.11)	-0.91 (1.46)+
L1-F-PLS	8.19 (1.53)	1.06 (1.08)+	6.96 (1.07)	3.44 (1.47)	3.83 (1.00)
S71-S-OK	-8.09 (0.80)	9.96 (0.77)	2.41 (0.78)	1.20 (0.88)	10.92 (1.25)
S72-S-OK	-9.96 (0.76)	8.11 (0.78)	0.15 (1.12)+	-0.86 (0.84)+	8.47 (1.21)
S7-S-PFS	-10.93 (0.90)	8.72 (0.80)	-3.68 (0.73)	-1.93 (0.99)	4.32 (1.25)
S8-F-OK	-12.45 (0.75)	8.74 (0.74)	-5.99 (1.06)	-3.61 (0.83)	1.82 (1.15)+

Note: + not significantly different from zero at the 5% level

Table 9.11: Estimates of the percentage bias in the estimates of the parameters and variables used in the management of ICSEAF hake stocks for selected estimation procedures listed in Table 9.5. The standard error of each bias estimate (expressed as a percentage) is given in parenthesis. Column 1 contains the acronym for each procedure. The following lengths of "serial correlation" data (see Chapter 7) after the original catch-effort series (i.e. starting in year 22, or "1986") are used :

Table	Number of years of "serial correlation"
a	5 Years
b	7 Years
c	10 Years

9.11(a): 5 years of "Serial Correlation"

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	19.35 (1.16)	8.28 (1.03)	26.53 (1.68)	14.11 (1.11)	19.03 (1.58)
BA-S-OK	-18.38 (0.73)	4.75 (0.73)	-14.88 (0.95)	-10.13 (0.80)	-7.80 (1.03)
BA-S-PLS	17.79 (1.22)	11.13 (0.93)	21.02 (1.50)	12.62 (1.42)	13.83 (1.41)
L1-F-PLS	7.32 (1.24)	1.14 (0.95)+	6.21 (1.44)	2.60 (1.18)	3.46 (1.46)
L1-F-PEU	51.69 (2.44)	25.93 (1.56)	51.75 (4.16)	45.03 (2.38)	55.34 (4.73)
S71-S-OK	-11.40 (0.82)	5.27 (0.89)	-5.78 (1.16)	-2.45 (0.90)	2.06 (1.26)+
S7-S-PFS	-11.20 (0.75)	5.70 (0.73)	-10.92 (1.02)	-5.53 (0.83)	-3.51 (1.11)

Note: + not significantly different from zero at the 5% level

9.11(b): 7 Years of "Serial Correlation"

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	19.46 (1.17)	8.93 (1.01)	23.47 (1.66)	14.22 (1.12)	16.14 (1.56)
BA-S-OK	-15.22 (0.69)	2.14 (0.76)	-10.61 (1.03)	-6.66 (0.76)	-3.17 (1.12)
BA-S-PLS	-18.79 (0.71)	4.56 (0.67)	-15.33 (0.95)	-10.58 (0.78)	-8.29 (1.03)
L1-F-PLS	8.06 (1.22)	2.12 (0.87)	6.48 (1.37)	3.31 (1.16)	3.91 (1.35)
L1-F-PEU	43.22 (2.96)	22.89 (1.86)	373.29 (241.10)+	36.93 (2.83)	437.94 (285.61)+
S71-S-OK	-10.37 (0.79)	6.47 (0.83)	-6.08 (1.01)	-1.31 (0.87)+	1.73 (1.09)+
S7-S-PFS	-13.89 (0.73)	5.94 (0.66)	-10.49 (0.94)	-5.19 (0.80)	-3.04 (1.01)

Note: + not significantly different from zero at the 5% level

9.11(c): 10 Years of "Serial Correlation"

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
BA-F-OK	15.04 (0.92)	6.34 (0.83)	17.49 (1.11)	9.99 (0.88)	10.51 (1.28)
BA-S-OK	-17.48 (0.67)	0.52 (0.73)+	-13.36 (1.11)	-9.14 (0.74)	-6.15 (1.20)
BA-S-PLS	-19.32 (0.78)	3.89 (0.69)	-15.96 (1.00)	-11.17 (0.86)	-8.98 (1.09)
L1-F-PLS	7.22 (1.21)	1.46 (0.82)+	5.74 (1.35)	2.51 (1.15)	3.35 (1.36)
L1-F-PES	30.00 (2.17)	16.67 (1.39)	*	24.29 (2.08)	*
S71-S-OK	-13.30 (0.73)	4.12 (0.77)	-9.30 (1.03)	-4.54 (0.80)	-1.75 (1.12)+
S7-S-PFS	-15.12 (0.75)	4.93 (0.64)	-11.89 (0.94)	-6.54 (0.82)	-4.56 (1.02)

Note: + not significantly different from zero at the 5% level
* bias exceeds 1000%

Table 9.12: Means and 95% confidence limits for the "true" biomass estimated by selected estimation procedures, after management over a period of 10 years of a stock described by the Butterworth age-structured operating model. The biomass at the beginning of this period is 55% of K.

Estimation Procedure	Mean and 95% confidence interval for the biomass after 10 years	
Babayan *et al.* Linear Method Unsmoothed cpue data (Bn-F-GLU)	31%K	(8%K , 55%K)
Butterworth-Andrew (Fox form) y_1 = K (BA-F-OK)	48%K	(34%K, 96%K)
Butterworth-Andrew (Schaefer form) y_1 = K (BA-S-OK)	53%K	(40%K, 71%K)
Lleonart *et al.* q estimated Unsmoothed cpue data (Fox form) (Ll-F-PEU)	42%K	(22%K, 62%K)
Lleonart *et al.* Linear Method Smoothed cpue data (Fox form) (Ll-F-PLS)	51%K	(37%K, 66%K)
Schnute-77(1) y_1 = K (S71-S-OK)	52%K	(41%K, 68%K)

Table 9.13: Estimates of the percentage bias in the estimates of the parameters and variables used in the management of ICSEAF hake stocks when the Butterworth-Andrew (Fox form) (y_1 = K) observation error estimator (BA-F-OK) is used to estimate the variables (and parameters) after a period in which catches are set to the arithmetic average of those predicted by the three estimation procedures currently used by ICSEAF (Bn-F-GLU, BA-F-OK, and Ll-F-PEU). The standard error of each bias estimate (expressed as a percentage) is given in parenthesis.

Years of Serial Correlation	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
5	16.72 (1.36)	6.56 (1.23)	24.32 (1.78)	11.60 (1.30)	16.96 (1.67)
7	17.09 (1.13)	7.64 (1.10)	18.14 (1.37)	11.95 (1.08)	11.14 (1.29)
10	15.13 (1.52)	6.98 (1.34)	32.13 (18.89)+	10.07 (1.46)	24.33 (17.81)+

Note: + not significantly different from zero at the 5% level

Table 9.14: Estimates of the percentage bias in the estimates of the variance of selected variables used in the management of the ICSEAF hake stocks for different variance estimation procedures. Standard errors of these bias estimates are given in parenthesis. In each simulation trial, the model estimation procedure is the same as the operating model. Tables (a) to (d) contain the results of the following simulations :

Table	Quantity estimated
a	S.e. of $\hat{E}_{0.1}$
b	C.v. of $\hat{E}_{0.1}$
c	S.e. of $\hat{Q}_{0.1}$
d	C.v. of $\hat{Q}_{0.1}$

9.14(a): S.e. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	10.01 (1.76)	117.39 (6.98)	-73.54 (2.01)
Infinitesimal Jack-knife	96.91 (3.07)	559.83 (11.15)	-69.69 (0.80)
"Naive" Bootstrap	51.76 (2.53)	*	-57.58 (2.51)
Permuted "Naive" Bootstrap	74.57 (13.32)	*	-55.08 (2.52)
(Conditioned) Parametric Bootstrap	5.66 (1.55)	-6.74 (2.34)	-80.93 (1.13)
Information Matrix	27.11 (1.86)	214.78 (11.33)	*

Note: * the bias exceeds 1000%

9.14(b): C.v. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	9.74 (1.62)	113.04 (4.96)	-74.52 (3.54)
Infinitesimal Jack-knife	96.43 (2.81)	449.45 (63.02)	-69.48 (0.88)
"Naive" Bootstrap	51.71 (2.43)	*	-55.99 (3.86)
Permuted "Naive" Bootstrap	74.17 (13.25)	*	-53.11 (3.88)
(Conditioned) Parametric Bootstrap	5.34 (1.38)	-7.84 (1.56)	-81.20 (1.14)
Information Matrix	26.85 (1.69)	200.55 (4.99)	*

Note: * the bias exceeds 1000%

9.14(c): S.e. of $\hat{Q}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	10.21 (1.68)	92.02 (6.53)	-26.79 (3.68)
Infinitesimal Jack-knife	91.09 (2.79)	504.61 (108.65)	-35.20 (2.90)
"Naive" Bootstrap	42.98 (2.19)	*	-18.71 (3.39)
Permuted "Naive" Bootstrap	50.95 (7.34)	*	-8.07 (3.86)
(Conditioned) Parametric Bootstrap	2.67 (1.37)	-17.05 (1.82)	566.60 (70.06)
Information Matrix	68.33 (2.02)	193.75 (11.16)	140.79 (14.64)

Note: * the bias exceeds 1000%

9.14(d): C.v. of $\hat{Q}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	10.55 (1.64)	87.24 (4.44)	-14.28 (63.54)+
Infinitesimal Jack-knife	91.54 (2.64)	399.02 (60.63)	-25.95 (53.60)+
"Naive" Bootstrap	43.97 (2.30)	*	-12.14 (75.97)+
Permuted "Naive" Bootstrap	51.73 (7.45)	*	22.10 (78.69)+
(Conditioned) Parametric Bootstrap	2.96 (1.31)	-16.84 (1.39)	740.36 (184.54)+
Information Matrix	66.41 (2.08)	180.02 (5.10)	24.99 (209.15)+

Note: * the bias exceeds 1000%
+ not significantly different from zero at the 5% level

Table 9.15: Estimated percentage bias in the estimates of the c.v. and s.e. obtained using improvements [see equation (6.17)] to the (conditioned) parametric bootstrap method of variance estimation when applied to the Babayan *et al.* estimation procedure (Bn-F-GLU). The standard error of each percentage bias estimate is given in parenthesis.

Management Variable	Options in the Parametric Bootstrap Method		
	σ is variable n = 250	σ constrained n = 250	σ constrained n = 1000
s.e. $(\hat{E}_{0.1})$	-80.93 (1.13)	-65.02 (3.09)	-64.94 (3.12)
c.v. $(\hat{E}_{0.1})$	-81.20 (1.14)	-69.43 (4.61)	-69.41 (4.67)
s.e. $(\hat{Q}_{0.1})$	566.60 (70.06)	-75.14 (0.95)	-75.18 (0.93)
c.v. $(\hat{Q}_{0.1})$	740.36 (184.54)	-71.45 (2.96)	-71.33 (2.99)

9.16(a): S.e. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-36.60 (1.11)	32.23 (3.19)	-6.03 (3.27)+
Infinitesimal Jack-knife	20.49 (2.04)	*	27.12 (0.91)
"Naive" Bootstrap	??	*	3.71 (2.46)+
Permuted "Naive" Bootstrap	2.73 (4.19)+	*	18.63 (3.75)
Punt No 1 Bootstrap	??	236.91 (92.06)	*
Punt No 2 Bootstrap	-58.56 (0.75)	-65.77 (0.96)	*
Punt-DSB Bootstrap	??	*	*
(Conditioned) Residual Bootstrap	??	-41.89 (1.05)	-64.21 (1.20)
(Conditioned) Parametric Bootstrap	-40.52 (1.30)	-25.66 (1.31)	-56.57 (1.40)
Information Matrix	??	84.66 (5.44)	*

Note: * the bias exceeds 1000%
+ not significantly different from zero at the 5% level
?? one of the simulation trials resulted in an error

9.16(b): C.v. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-37.42 (0.98)	73.05 (20.10)	-10.88 (3.23)
Infinitesimal Jack-knife	9.12 (1.58)	*	*
"Naive" Bootstrap	??	*	1.74 (2.56)+
Permuted "Naive" Bootstrap	1.69 (4.10)+	*	18.45 (3.94)
Punt No 1 Bootstrap	??	109.25 (70.38)	*
Punt No 2 Bootstrap	-77.53 (0.41)	-66.07 (0.75)	*
Punt-DSB Bootstrap	??	*	*
(Conditioned) Residual Bootstrap	??	-39.66 (0.96)	-65.61 (1.26)
(Conditioned) Parametric Bootstrap	-37.13 (4.64)	-18.15 (2.69)	-59.08 (1.45)
Information Matrix	??	78.04 (2.60)	*

Note: * the bias exceeds 1000%
+ not significantly different from zero at the 5% level
?? one of the simulation trials resulted in an error

Table 9.17: Summary of the estimates of the percentage bias and expected discrepancy in the estimates of the c.v. of selected variables used in the management of the ICSEAF hake stocks, for different variance estimation procedures. The standard error of each bias/discrepancy estimate is given in parenthesis. The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A. Each entry in this Table represents is the average of the biases/discrepancies obtained for the three operating model error combinations considered.

Table	Quantity estimated
a	C.v. of $\hat{E}_{0.1}$
b	C.v. of $\hat{Q}_{0.1}$

9.17(a): C.v. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-31.96 (1.10)	-34.64 (2.11)	*
L1-F-PLS	-33.83 (1.08)	-54.67 (0.64)	-43.48 (0.89)
S71-S-OK	-17.51 (0.92)	??	-4.07 (1.07)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	45.99 (0.78)	50.23 (1.67)	*
L1-F-PLS	40.50 (0.75)	42.73 (0.57)	49.52 (0.59)
S71-S-OK	44.87 (0.71)	??	49.80 (1.31)

Note: * the bias exceeds 1000%
?? one of the simulation trials resulted in an error

9.17(b): C.v. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	3.08 (0.86)	-33.40 (1.86)	*
L1-F-PLS	-39.03 (1.04)	-48.91 (0.73)	-38.95 (0.76)
S71-S-OK	-39.87 (0.77)	??	-39.37 (0.91)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	45.98 (0.66)	46.88 (1.47)	*
L1-F-PLS	43.56 (0.75)	50.00 (0.62)	42.61 (0.54)
S71-S-OK	46.71 (0.61)	??	49.18 (0.57)

Note: * the bias exceeds 1000%
?? one of the simulation trials resulted in an error

Table 9.18: Estimates of the percentage bias and expected discrepancy in the estimates of the variance of selected variables used in the management of the ICSEAF hake stocks. Standard errors are given in parenthesis. The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A. The data series used for the simulations is restricted to the years 1965 to 1979. All artificial data sets used in the estimation of the biases are generated using σ_q = 0.1 and σ_r = 0.2. Tables (a) to (d) contain the results of the following simulations:

Table	Quantity estimated
a	S.e. of $\hat{E}_{0.1}$
b	C.v. of $\hat{E}_{0.1}$
c	S.e. of $\hat{Q}_{0.1}$
d	C.v. of $\hat{Q}_{0.1}$

9.18(a): S.e. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-77.55 (1.76)	-91.44 (2.26)	-77.37 (1.48)
L1-F-PLS	-58.50 (2.49)	-53.32 (2.18)	-95.34 (1.77)
S71-S-OK	-30.42 (3.14)	-43.46 (2.22)	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	79.91 (1.27)	95.28 (1.49)	77.66 (1.42)
L1-F-PLS	65.45 (1.66)	58.37 (1.57)	98.52 (0.81)
S71-S-OK	49.40 (1.95)	49.27 (1.66)	??

Note: ?? one of the simulation trials resulted in an error

9.18(b): C.v. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-73.52 (2.68)	*	-70.54 (3.06)
L1-F-PLS	-21.28 (34.12)+	-67.08 (44.35)+	-97.73 (0.77)
S71-S-OK	-17.78 (6.56)	-29.42 (5.54)	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	81.17 (1.56)	*	78.95 (2.07)
L1-F-PLS	107.27 (33.46)	178.81 (43.09)	98.38 (0.29)
S71-S-OK	63.71 (5.30)	64.66 (4.17)	??

Note: + not significantly different from zero at the 5% level
* the bias exceeds 1000%
?? one of the simulation trials resulted in an error

9.18(c): S.e. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-66.50 (1.97)	-88.76 (2.83)	-68.11 (1.81)
L1-F-PLS	-61.28 (2.47)	-53.79 (2.06)	-94.61 (1.92)
S71-S-OK	-15.36 (2.97)	-34.45 (2.09)	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	68.12 (1.73)	94.38 (1.97)	69.27 (1.62)
L1-F-PLS	68.21 (1.58)	58.08 (1.52)	98.37 (0.88)
S71-S-OK	39.44 (1.87)	41.79 (1.45)	??

Note: ?? one of the simulation trials resulted in an error

Table 9.19: Estimates of the percentage bias and expected discrepancy in the estimates of the variance of selected variables used in the management of the ICSEAF hake stocks. Standard errors are given in parenthesis. The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A. Ten years of "serial correlation" data following the end of the given catch-effort data series are included in each simulation. All artificial data sets used in the estimation of the biases are generated using $\sigma_q = 0.1$ and $\sigma_r = 0.2$. Tables (a) to (d) contain the results of the following simulations:

Table	Quantity estimated
a	S.e. of $\hat{E}_{0.1}$
b	C.v. of $\hat{E}_{0.1}$
c	S.e. of $\hat{Q}_{0.1}$
d	C.v. of $\hat{Q}_{0.1}$

9.19(a): S.e. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-39.76 (3.59)	-44.50 (1.17)	-50.30 (1.15)
L1-F-PLS	-51.24 (1.08)	-51.33 (1.00)	-38.69 (1.85)
S71-S-OK	-39.78 (1.48)	??	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	47.46 (3.19)	45.42 (1.02)	50.95 (1.03)
L1-F-PLS	51.86 (0.96)	51.57 (0.95)	43.96 (1.29)
S71-S-OK	42.47 (1.14)	??	??

Note: ?? one of the simulation trials resulted in an error

9.19(b): C.v. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-40.91 (2.62)	-44.14 (1.24)	-50.44 (1.06)
L1-F-PLS	-50.92 (0.99)	-51.83 (0.73)	-40.15 (1.35)
S71-S-OK	-39.93 (1.35)	??	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	46.41 (2.23)	45.89 (0.95)	51.16 (0.91)
L1-F-PLS	51.05 (0.96)	51.83 (0.73)	42.26 (1.06)
S71-S-OK	41.63 (1.12)	??	??

Note: ?? one of the simulation trials resulted in an error

9.19(c): S.e. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-11.71 (5.52)	-23.55 (1.37)	-20.45 (1.82)
L1-F-PLS	-50.02 (1.14)	-48.01 (0.89)	-23.00 (1.54)
S71-S-OK	-17.30 (1.96)	??	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	34.71 (5.11)	27.95 (0.98)	28.21 (1.34)
L1-F-PLS	50.62 (1.03)	48.08 (0.87)	29.57 (1.00)
S71-S-OK	29.96 (1.21)	??	??

Note: ?? one of the simulation trials resulted in an error

9.19(d): C.v. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-8.49 (2.75)	-16.00 (1.63)	-14.26 (1.63)
L1-F-PLS	-50.64 (1.10)	-48.94 (0.76)	-25.99 (1.23)
S71-S-OK	-14.77 (1.99)	??	??

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	27.26 (2.21)	25.07 (1.07)	24.20 (1.05)
L1-F-PLS	50.74 (1.08)	48.99 (0.76)	29.03 (0.92)
S71-S-OK	29.21 (1.19)	??	??

Note: ?? one of the simulation trials resulted in an error

10 DISCUSSION

10.1 Management variable estimation procedures

10.1(a) The procedures in current use by ICSEAF

The model estimation procedures compared in this study have been shown, in general, to produce positively biased estimates of MSY, control effort and quotas. In particular, all three procedures currently in use by ICSEAF for the management of the southern African hake resources [i.e. the Butterworth-Andrew (Fox form) y_1 = K observation error estimator, the Lleonart *et al.* (Fox form) q estimated (with unsmoothed cpue data) process error estimator and the Babayan *et al.* (Fox form) Linear Method (using unsmoothed cpue data)] show substantial upward bias (relative to the Butterworth age-structured operating model) in their estimation of the management variables, for all error type combinations considered (Appendices A to C). As the Butterworth age-structured operating model is a more realistic representation of the underlying dynamics of the stock than the simplified models on which the estimators are based, the results suggest that the continued use of these procedures can be expected to result in overexploitation of the stock (at least in the short-to-medium term), and should be questioned.

The results in Table 9.1 and Appendices A to C may seem to be contradictory - in Table 9.1 the BA-F-OK procedure appears to be unbiased, whereas in Appendices A to C substantial biases are reported. This is, of course, a reflection of the fact that different operating models are being used: in Table 9.1 the operating models are identical to the models on which the estimation procedures are based, whereas in the Appendices the Butterworth age-structured operating model is used. This comparison does, however, serve to illustrate the difference (alluded to in Section 1.2) between bias due to estimation error (Table 9.1) and "error due to approximation" (Appendices A to C).

10.1(b) The effects of age-structure on the performance of production model estimation procedures

The results of this analysis suggest that quota and biomass estimates produced by the procedures using only catch-effort data are positively biased (see Fig 9.1). This may partially resolve the differences between quota estimates produced by these production model approaches and those evaluated from VPA results. [Butterworth *et al.* (1986a) report estimates of $Q_{0.1}$ for the various ICSEAF hake stocks (obtained using VPA coupled with yield-per-recruit methods) that lie between 28% and 74% of the corresponding estimates obtained using the Butterworth-Andrew (Schaefer form) y_1 = K observation error estimator (BA-S-OK).]

Bias in the estimation of the true equilibrium surplus production function by the approaches described above (see Figures 9.2 to 9.7) may be a result of the lack of structure in the production model formulations, which frustrates attempts to capture the age-structure dynamics. The more realistic age-structured models behave differently from the traditional simple surplus production model approximations. Figure 10.1 illustrates this - the effective surplus production of the resource during each year, $G_i^{eff}(y_i)$, is determined from the biomass series generated by the age-structured operating model as follows :

$$G_i^{eff}(y_i) = y_{i+1} - y_i + C_i \qquad (10.1)$$

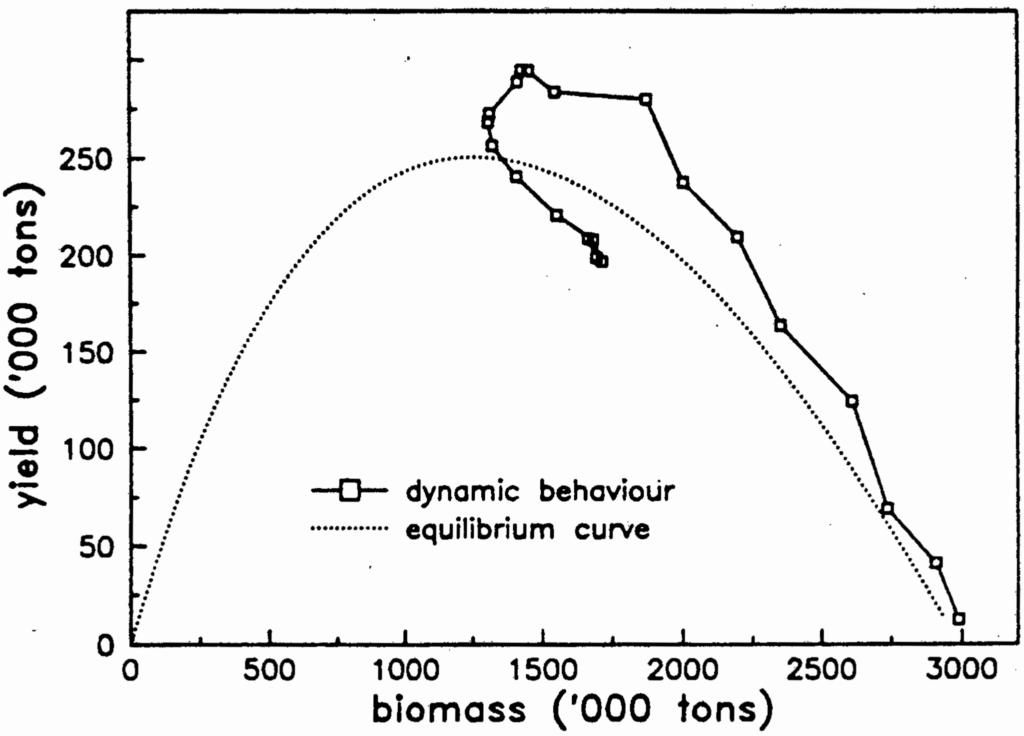


Figure 10.1: The equilibrium surplus production curve for the (deterministic) age-structured operating model and the time series of effective annual surplus production generated dynamically by the model under the given annual catch series from 1965 to 1985.

[Note that the operating model used here is the deterministic (i.e. $\sigma_r = \sigma_q = 0$) form of the Butterworth age-structured operating model.] This is compared with the equilibrium surplus production curve $G^{eqm}(y)$ corresponding to the operating model (which is determined by setting a fixed fishing mortality and allowing the age structure to adjust to the corresponding equilibrium).

For the initial years in the data series, $G^{eff} > G^{eqm}$; later (shortly after the biomass trend reverses), the inequality changes sign, but it is clear from inspection of Figure 10.2 that this reversal does not provide sufficient compensation to remove the positive bias in the Butterworth-Andrew (Schaefer form) $y_1 = K$ observation error procedure (BA-S-OK) estimate of MSY (and consequently of $Q_{0.1}$). The reason for this is that the procedure is effectively fitting a $G^{eqm}(y)$ curve to the $G_i^{eff}(y_i)$ data points, and consequently estimates a value for MSY which is too large.

Procedures (such as those investigated here, except for the ones based on the Schnute-85 model) which assume that surplus production is determined only by current biomass cannot achieve high accuracy in representing biomass trajectories when the effects illustrated in Figure 10.1 are present. The negative nature of this comment is, however, slightly misleading because, although none of the model estimation procedures considered here is able to reproduce the "true" biomass signal exactly, or is able even to estimate the complete (equilibrium) surplus production function correctly, some of them are nevertheless able to estimate management variables reasonably

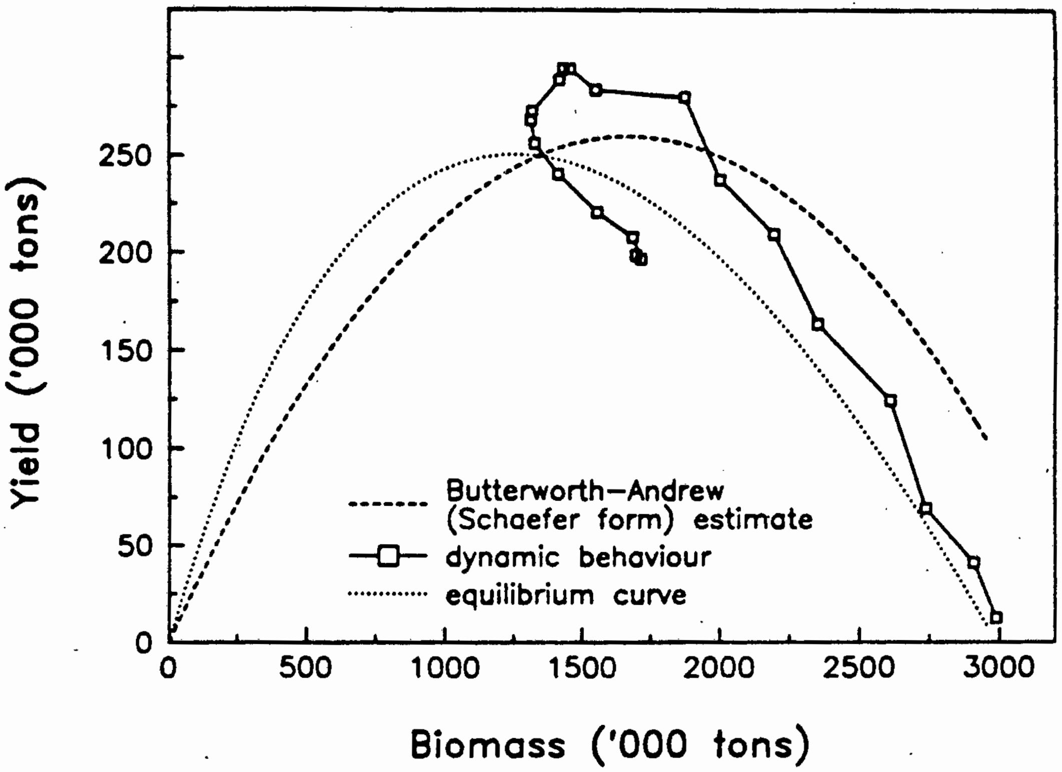


Figure 10.2: The plots of Figure 10.1 together with the surplus production curve estimated by the Butterworth-Andrew (Schaefer form) y_1 = K observation error estimator (BA-S-OK) applied to data generated by the age-structured operating model.

accurately, although this accuracy may vary with the length of the data series.

10.1(c) The Babayan *et al.* time series methods

Probably the major source of error in the Babayan *et al.* time series methods is the use of Gulland's (1961) regression procedure to estimate E_{MSY}, MSY and $E_{0.1}$. This method has previously been shown (Butterworth and Andrew 1987a, Butterworth 1988a) to produce positively biased estimates when applied to the catch-effort data for the ICSEAF hake stocks, a finding which illustrates a general characteristic of stocks exhibiting a declining cpue trend, as has been reported by many authors including Hilborn (1979), Mendelssohn (1980), Mohn(1980), Roff and Fairbairn (1980), Stocker and Hilborn (1981), Walters (1986), and Polacheck and Hilborn (1988). Any estimation procedures based on the Gulland regression method should therefore be rejected. In addition, Butterworth (1988c) suggests that using a shorter data series for the time series component of the Babayan *et al.* time series estimators may result in greater variance in the predictions of cpue for the next year. This opinion is supported by the observation that the s.e.'s of Q_{MSY} and $Q_{0.1}$ in Tables A(1), A(2) to C(1), C(2) are much larger than those of model parameters (E_{MSY}, $E_{0.1}$ and MSY) which do not depend on the current cpue.

The estimates of quotas produced by the Babayan *et al.* time series approaches are therefore substantially biased (as the Gulland procedure is used to estimate the target effort level) as well as highly variable [as a short cpue series is used to estimate (usually) more than two parameters]. In addition, it is shown in Section 9.4(b) that it is likely that implementation of the Babayan *et al.* (Linear Method) procedure (Bn-F-GLU) will cause the hake resource in Divisions 1.3 + 1.4 to become markedly biologically overexploited (i.e. driven well below its MSY level) within 10 years, if this method is used by ICSEAF as the sole means of estimating quotas. The comment made by Babayan and Kizner (1988) that such time series methods allow "a practically unlimited enhancement of the TAC estimate reliability" is therefore not supported by this investigation.

10.1(d) The Deriso/Schnute-85 methods

Although Figure 10.1 appears to suggest that incorporation of age-structure should improve the accuracy of the estimates, the Schnute-85 procedure [which is a generalisation of the Deriso (1980) approach and does to some extent incorporate these effects] is unable even to reproduce the biomass trend (see Figure 9.1). The probable explanation for this poor performance may lie in the summation in equation (5.21), which results in the numbers-at-age (for ages greater than nine) being greater than zero; in contrast, the age-structured operating model ignores fish older than nine years (virtually absent from the catch for the real resource), essentially assuming that M becomes infinite after this age. [Appendix 10.A discusses how this conclusion is reached.]

The results obtained here regarding the performance of estimation procedures based on the Deriso/Schnute-85 model are consistent with those obtained in similar analyses undertaken by Ludwig and Walters (1985) and ICES (1987). The fact that such procedures were unable to estimate their own parameters adequately in these studies (see Section

8.3) indicates that substantial "error due to estimation" was present; they are therefore extremely unlikely to perform satisfactorily. In the implementation considered here, the Schnute-85 procedure was used to estimate only three parameters, the values of the others being provided by auxiliary information (see Section 5.8). Even so, however, the results obtained remain indicative of a poor estimator.

In addition, in certain of the robustness tests, the Schnute-85 procedure was unable to estimate the model parameters, which remained set at their initial values. After investigating the sum of squares (SS) surface, it was discovered that the SS does not depend strongly on the parameter a, a feature which apparently causes the non-linear minimisation algorithm to stop at a point which is not the minimum of SS, although the algorithm indicates that a minimum has been found. The biases and discrepancies reported here for the Schnute-85 procedure (Appendices A to E) may thus be somewhat inflated and the s.e.'s substantially deflated; the initial values set were close to the minimum of the SS, however, so that the effect on the biases may nevertheless be small.

It is concluded that the Schnute-85 procedure (as applied in the context of this study) should be rejected, as any estimation scheme which employs single precision arithmetic is likely to suffer numerical estimation problems if this estimator is used. Further investigation is required to determine whether normalising the parameters for the minimisation algorithm or re-parametrisation of the model may produce a more reliable performance by the fitting procedure. The use of double precision arithmetic should also be investigated.

10.1(e) The value of auxiliary information

The main reason for the poor performance of many of the model estimation procedures lies in the attempt to estimate too many parameters. Observation error estimators which attempt to estimate more than three parameters (e.g. the Horbowy-Draganik and Lleonart *et al.* estimators, and all procedures which estimate y_1) are unable to estimate these parameters with any reasonable degree of precision (Appendices A to C). Process error estimators which estimate q directly in the data fitting procedure [e.g. the Lleonart *et al.* (1985a) procedure (Ll-F-PEU)] are also all extremely imprecise and inaccurate (Appendices A to C). This statement may be slightly misleading, as it appears to suggest that observation error estimators are able to estimate more parameters than are process error estimators. In fact, each error model can be considered to require estimates of (at least) four parameters (y_1, q and two surplus production function parameters) where, in the case of process error models, the estimates of y_1 are produced by the formula $(C/E)_1/\hat{q}$. At this level, both process and observation error estimators perform poorly. However (as discussed further below), when the number of parameters is reduced by one through use of the auxiliary information that, at the start of the data series, the stock was at its unexploited equilibrium value (fixing $y_1 = K$ for the observation error estimators, or some variant of $(C/E)_1 = qK$ for the process error estimators), both sets of estimators are able to estimate the remaining three parameters adequately for the catch-effort data set considered here.

Butterworth and Andrew (1987a) have argued that the procedure suggested by Lleonart *et al.* (1985a) (Ll-F-PEU) provides very imprecise estimates. This can now be explained as the result of attempting to estimate the parameter α (the unexploited equilibrium cpue) in the non-linear optimisation process, without the use of auxiliary information - a technique which is shown here [Tables A(7) and B(7)] to result in imprecise estimates. In addition, the bias of $\hat{E}_{0.1}$ for this procedure (see Figure 9.5) is far smaller when it is estimated from the deterministic data than from the stochastic simulations; this difference can be attributed to the imprecision and distributional skewness of the estimator. Replacement of this procedure by the Lleonart *et al.* (Fox form) Linear Method (with smoothed cpue data) process error estimator (Ll-F-PLS) is therefore advocated. In general, however, pre-smoothing of the cpue series does not appear to improve the estimates substantially, and has the disadvantage of complicating the variance estimation procedures.

Butterworth (1988c) reports that the Babayan-Kizner (Fox form) (q estimated) process error estimator (BK-F-PEU) produces estimates which are far less precise than those produced by the corresponding Butterworth-Andrew observation error estimator, and suggests that this may be a general feature of process error - as opposed to observation error estimators. This comparison is, however, not entirely fair, as the observation error estimator in this case was provided with the additional information that $y_1 = K$. As discussed above, when process error estimators are given similar auxiliary information (i.e. an independent estimate of α), they can be shown to compare far more favourably with observation error estimators.

The incorporation of auxiliary information, and specifically estimates of α, whether directly (for process error estimators) or via the equivalent $y_1 = K$ assumption (for observation error estimators), increases the accuracy and precision of the estimates of management-related quantities obtained. [In the case of process error estimators, setting α to the value of its linear approximation (i.e. using the Linear Method) appears to result in the best performance of the three alternative methods tested.]

10.1(f) The robustness of different surplus production functional forms

The argument of Ludwig *et al.* (1988) has been examined here, i.e. that a model estimation procedure which is based on the Ricker form of the surplus production function is more robust than the same procedure which is based on the Power model, and the Butterworth-Andrew (Schaefer form) $y_1 = K$ TLS estimator (BA-S-TK) was found to be superior to the Ricker $y_1 = K$ TLS estimator (BA-R-TK) advocated by Ludwig *et al.* (1988) [Tables A(12), B(12) and C(12)]. In general, procedures based on certain of the surplus production functional forms (e.g. the Schaefer and Ricker forms) are able to perform consistently better than those based on other forms (e.g. Power, Fox, Beverton-Holt and Pella-Tomlinson), even under the tests for robustness to changing the B_{MSY}/K parameter in the operating model [Tables D(15) and D(16) and Appendix E]. This suggests that the former surplus production functional forms may be more robust representations of the underlying age-structured model, an observation which requires further investigation (using different operating models and data sets, for example) before firm conclusions can be drawn. Altering the length of the data series [which has been shown (Table 9.10) to have a considerable effect on the relative performance of the different estimators] may also influence this result.

10.1(g) Effects of "serial correlation" and data contrast

It is not clear from the results whether the "serial correlation" effect raised by Butterworth (1988a) (see Section 6.1) is likely to increase the bias of the management variable estimates; in any case, any such bias will tend to be damped out as the length of the data series increases. In addition, the fact that the bias of these quantities does not decrease substantially when the mean of the three model estimation procedures currently used by ICSEAF is used to set quotas suggests that the "serial correlation" problem does not affect management variable estimates substantially. Nevertheless, what is clear (see Figures 10.3 and 10.4) is that (in general) the reversal in the underlying biomass trend has a critical effect on the success of the model estimation procedures, as a result of the increased contrast in the data series, and that this generally results in greater accuracy and precision in the management variable estimates [see Tables 9.10(a) to (e)]. Even so, it does appear that the bias of the estimates produced by some of the procedures may increase as the data series is extended.

Figure 10.3 shows the Butterworth-Andrew (Schaefer form) $y_1 = K$ observation error estimator (BA-S-OK) fit to the data from 1965 to 1979. This procedure attempts to ensure that the maximum value of $G^{eff}(y)$ ($\approx$ 300) falls close to the surplus production curve, thereby

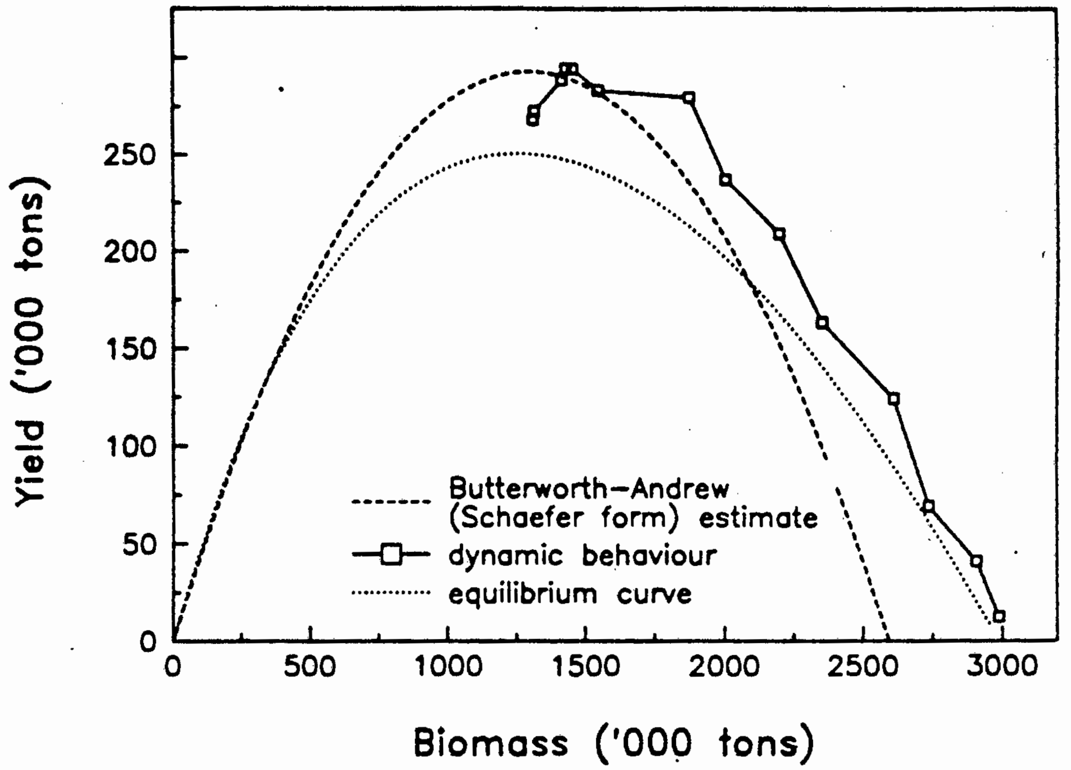


Figure 10.3: This plot is identical to Figure 10.2, except that the effective annual surplus production generated dynamically by the operating model is taken only up to 1979, and the BA-S-OK estimator is applied to the corresponding data only.

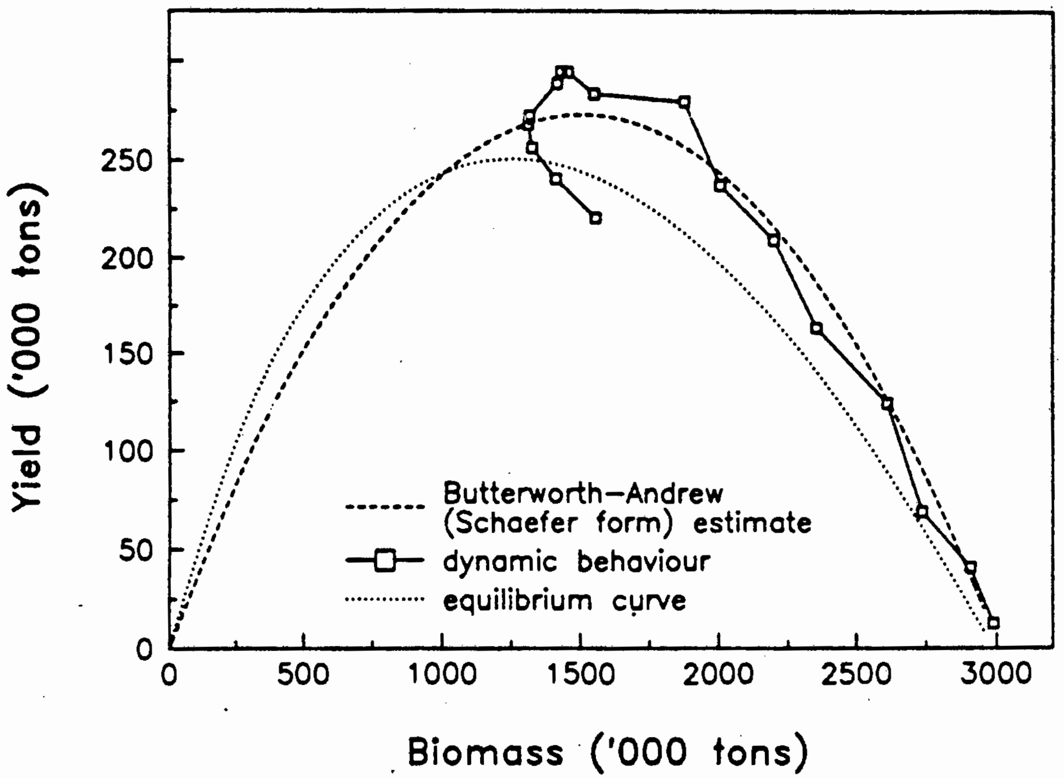


Figure 10.4: This plot is identical to Figure 10.2, except that the effective annual surplus production generated dynamically by the operating model is taken only up to 1982, and the BA-S-OK estimator is applied to the corresponding data only.

forcing it upwards. It appears that the data points below this maximum do not have much effect on the determination of the curve. When more data are added (Fig. 10.4), the effect is to pull the surplus production curve down, which results in a much better fit to $G^{eqm}(y)$ and hence improved estimates of MSY (though this may be an accident of the operating model parameters and catch data series chosen, and not necessarily a general result). Further and extensive investigation into the robustness of model estimation procedures to the length of the data series is thus required, because the "best" procedures are selected here on the basis of an analysis carried out on data from 1965 to 1985, whereas it may transpire that the performance of some or all of these procedures deteriorates substantially when further years of data are added.

10.1(h) Some surprising results

Although Mohn (1980) reports that estimation procedures based on the Schnute-77 model may fail hopelessly when a substantial amount of observation error is present, this has not been observed for any of the simulations in this study, even though the amount of catch-effort data contrast in Mohn's study appears to be larger. The probable explanation for this is that, in this study, estimates of MSY and E_{MSY} are not permitted (by the nature of the algorithm used to estimate the parameters - see Chapter 5) to become negative; this may result in a much smaller chance of estimation failure.

An observation which is difficult to reconcile with the results presented here is that Butterworth and Andrew's (1987b) estimates of MSY and $Q_{0.1}$ produced by the Schaefer form of the Butterworth-Andrew

y_1 = K observation error estimator (BA-S-OK) are larger than those provided by the Fox form of this estimator (BA-F-OK), for all of the ICSEAF hake stocks (Divisions 1.3+1.4, 1.5, 1.6, and 2.1+2.2). In contrast, the results of this study show that the Schaefer estimates are less positively biased than those produced by the Fox form. In order to investigate this apparent anomaly, the estimates of MSY for a set of 250 simulation trials (in which σ_q = 0.1 and σ_r = 0.2) were evaluated. It transpires that in 20% of these simulations, the MSY estimate produced by the Schaefer form of the BA-OK estimator is smaller than that produced using the Fox form. In addition, the Fox form occasionally produces estimates of MSY with very high positive deviation, indicating that the distribution of the estimates may be more skewed than the corresponding distribution for the Schaefer form.

Thus, one case (or perhaps even two) of actual Schaefer form MSY estimates being higher than the corresponding Fox form estimates is not exceptional, even given the greater positive bias of the latter, although this effect would be statistically significant if it occurred for all four stocks, as reported by Butterworth and Andrew (*op. cit.*). It merits further investigation, however, and may be linked to the appearance of markedly positive residuals in model fits to the early cpue values, which are consistent features in analyses of the real data sets.

10.2 Variance estimation procedures

10.2(a) Reasons for the failure of some of the variance estimation procedures

Surprisingly, the variance estimators compared are all unsuccessful, to a lesser or greater extent, in their estimation of the variance of the estimates of the management variables. However, a similar study by Efron (1981) indicates that large percentage biases may occur when variance estimators are applied to small data sets. Possible reasons for this include :

(i) in most of the simulations, $\hat{\sigma}$ [as calculated using formula (6.18)] is less than the "true" σ, indicating that this formula constitutes a biased estimator, possibly due to positive serial correlation in the cpue data, which has the effect of reducing the number of degrees of freedom; in such a case, (n-p) would be an overestimate of the degrees of freedom, and SS/(n-p) negatively biased as a result,

(ii) in a very few of the simulations, estimates of variance result which are clearly outliers and would be rejected should they occur in the analysis of a real data set; these outliers have a substantial influence on the estimates of bias obtained.

The failure of the information matrix method to produce unbiased estimates could conceivably be due to numerical approximation error in the computation of the partial derivatives (see Section 6.6). Equation (6.21) itself is also only an approximation, however, and furthermore, the considerable non-normality of the "true" distributions of the management variable estimates generally corresponds to a sum-of-squares surface which becomes markedly non-quadratic while still relatively close to the minimum, so that at best this method can only be approximate.

The "naive" (unconditioned) and *ad hoc* bootstrap methods tested fail to produce the accuracy that might have been expected of them in the light of other studies, such as that of Efron (1981). This is easily explained, however, as these methods were never designed to handle regression type problems, and it is unlikely that increasing either the length of the data series or the number of bootstrap samples would improve their performance. These procedures should thus not be used to estimate variances for quantities estimated by surplus production models.

Using a (conditioned) bootstrap procedure to estimate s.e.'s and c.v.'s (in combination with one of the percentile methods for estimating confidence intervals) appears to be the more successful and theoretically defensible approach, as these methods take into account (to a degree) the underlying regression nature of the estimation, i.e. they allow for the fact that the estimates of interest have very different sensitivities to different values in the data series. While these bootstrap techniques may be reliable for variance ratio estimation between different model estimation procedures, the dependence of bias on the error structure of the operating model leads to problems if an unbiased estimate of variance is required. Avoidance of such problems requires information on the ratio of process to observation error variance for the real resource - a quantity which may be difficult to assess.

The reason for the large biases in the estimates of precision when the operating model noise is predominantly process error (Appendices G, H, J and K) is that all the (conditioned) procedures implemented here are based on an assumed stochastic observation error structure [even in the case of the original Lleonart *et al.* procedure (Ll-F-PEU), which is a process error estimator]. The (conditioned) residual bootstrap method ensures this by virtue of equation (6.15), as does equation (6.19) for the (conditioned) parametric bootstrap. A process error form of this latter method which conditions on the catch series may be designed for the original Lleonart *et al.* procedure as follows, although (because the resultant equation cannot be solved explicitly for E_i^S) numerical evaluation is required:

$$(C/E)_1^S = (\widehat{C/E})_1 e^{\varepsilon_1}$$

$$(C/E)_i^S = [(1-q)\tilde{G}(E_i^S)/E_i^S + g(C/E)_{i-1}^S]e^{\varepsilon_i} \qquad (10.2)$$

In order to ensure that the artificially generated cpue values are realistic [scheme (10.2) allows for artificial cpue series which are very different from the original series], each artificially generated data series would be required to pass certain tests before being used in the variance estimation procedure. However, this variance estimation scheme requires further investigation to determine whether it merits being proposed as a candidate for exhaustive testing.

10.2(b) Implications for selection of a variance estimation procedure for use by ICSEAF

If an estimate of precision (such as the variance) is to be used as a basis for weighting the results from different model estimation procedures, then, if erroneous conclusions are to be avoided, such estimates of precision should either be unbiased, or the size of the bias should remain approximately constant for each model estimation procedure. Generally, for the model estimation procedure-variance estimation procedure combinations investigated here, the levels of bias have been found to be comparable (for any specific error combination chosen for the operating model). However, when the jack-knife method and the Lleonart *et al.* (q estimated) (Fox form) process error estimator (Ll-F-PEU) are used together, a positive rather than a negative bias arises. For this reason, caution should be exercised when pooling model estimates after weighting them by the inverse of their variance [as suggested by Butterworth and Andrew (1987a)] if the Ll-F-PEU (and probably also the Ll-S-PEU) procedure is one of those being used in combination with the jack-knife technique for estimating the variances.

In order to use the jack-knife method in such a case, any estimated variance would need to be multiplied by a "bias correction factor" for the model estimation procedure under consideration, to ensure that the variance estimates are unbiased relative to each other and are thus comparable. Computation of such corrected variance estimates would be problematical, however, as the appropriate "bias correction factors" depend on the particular error structure underlying the operating model (see Appendices F to K). In the light of this, it is recommended that either a single error structure be selected by ICSEAF, or a number of variance-bias-correction factors (henceforth referred to as correction factors) be computed for various possible error combinations. However, the results of this investigation suggest that it may be preferable to use a (conditioned) bootstrap method of variance estimation, as the associated biases (and discrepancies) appear to be less sensitive to the model estimation procedure used.

If difficulties are encountered by ICSEAF in the selection of one of the 10 methods of variance estimation presented here [possibly associated with the (computationally very intensive) calculation of correction factors (for differential bias) for variance estimation procedure - model estimation procedure combinations, it is possible to use the Butterworth age-structured operating model directly (with a selected error structure) to estimate the relative precision of model estimates. This method [which corresponds to a form of the (conditioned) parametric bootstrap] involves estimating the "true" variance of the quantity in question, using the operating model to generate data sets for the model estimation procedure under consideration (see Chapter 7). Although it bypasses the need for correction factors, there is a problem with this approach, as an operating model must be specified for every resource for which relative variance estimates for different model estimation procedures are required, involving (at least), the separate assessment of values for the parameters of each operating model.

Although this study indicates that the two conditioned bootstrap methods are equally accurate, the parametric form is preferred here as it has the flexibility to incorporate additional model assumptions (such as that the cpue points for the first year or two of the data series are outliers, and should be modelled as such) more easily.

Selection of an appropriate method of estimating confidence intervals is difficult, as the number of bootstrap simulations (250) used in this study to estimate the confidence limits is less than that (1000) recommended by Efron (1987) (because of realistic computing time constraints), and these estimates are therefore likely to be relatively imprecise. The standard simple method of computing confidence intervals (e.g. the 95% interval = ±2 s.e.'s) should be avoided, however, as the distributions of many of the variable and parameter estimates have been shown to be significantly skewed, indicating that the corresponding confidence intervals may be (highly) asymmetrical (see Tables 9.2 and 9.3). It would appear that use of the bias-corrected percentile method is more accurate than the percentile method, but verifying this would require more bootstrap simulations (by several orders of magnitude) than are required to obtain a single estimate of a confidence interval (Efron 1987). For the same reason, and also given the substantial biases in the variances of the management variables produced, it is not possible to comment with confidence on the precision of the different variance estimators considered in this study.

10.2(c) The effect of "serial correlation" on variance estimation

The "serial correlation" effect raised by Butterworth (1988a) appears to be insubstantial as a potential source of bias affecting variance estimation, in comparison with the size of other biases encountered here [although the degree of serial correlation could, of course, be estimated from the time series of residuals and subsequently incorporated into a (conditioned) parametric bootstrap procedure]. In addition, if probing experiments are to be implemented, these would be expected to reduce any serial correlation effect, as the catch in an experimental year will not depend strongly on the previous year's catch.

APPENDIX 10.A: ATTEMPTS TO ISOLATE THE MAJOR REASON FOR THE POOR PERFORMANCE OF THE SCHNUTE-85 ESTIMATION PROCEDURE WHEN APPLIED TO THE BUTTERWORTH AGE-STRUCTURED OPERATING MODEL

In order to determine why model estimation procedures based on the Schnute-85 model (which implicitly incorporates some age-structure effects) are unable to perform well, even when the data are generated by the deterministic version ($\sigma_q = \sigma_r = 0$) of the Butterworth age-structured operating model, the latter model was altered in an attempt to determine which of the difference(s) between these models is the most critical in respect of this poor performance. The particular form of the Schnute-85 procedure investigated was the (Fox form) $y_1 = K$ observation error estimator (S8-F-OK), which closely approximates the Butterworth age-structured operating model.

In order to remove obvious differences between the two models, the selectivity function in the Butterworth age-structured model was specified to represent knife-edge selectivity and the weights-at-age were altered to correspond exactly to those predicted by the Brody growth equation (5.20). When deterministic data were generated from this adjusted operating model, the Schnute-85 procedure fit appeared to be accurate (the SS was very small), although a comparison of actual and estimated biomass trends indicated that it was still relatively poor. As the (equilibrium) surplus production function for the Butterworth age-structured operating model is very similar to that for the Schnute-85 model, the only possible explanation for the latter's poor estimation performance seems to lie its assumption that the stock consists of an infinite number of age-classes, while the Butterworth age-structured operating model assumes only nine (which is consistent with the observation that very few fish older than age nine appear in the catches in Divisions 1.3 + 1.4). For a stock in unexploited equilibrium (with M = 0.3), the Schnute-85 model predicts the percentage-by-number of fish in the exploitable biomass which are greater than nine years of age as being 6.66%, i.e. minimal. However, this percentage increases substantially to 37% when the percentage-by-mass of the exploitable biomass aged over nine years is considered (as mass increases linearly with age), and this appears to be the main reason for the poor performance of the Schnute-85 estimation procedure when applied to data generated by the Butterworth age-structured operating model.

11 EXTENSIONS TO THE MODEL SELECTION METHOD

11.1 Extensions relating to catch-effort based procedures

11.1(a) Management variable estimation procedures

The procedures which have been investigated here do not encompass all possible models and methods by which the parameters of the those models could be estimated. Some other methods which merit investigation are:

(1) Time series methods [such as ARMA models (Box and Jenkins 1976)] could be used to model the residuals of dynamic model fits to the cpue data to improve the estimation of the cpue for the forthcoming year $(C/E)_{n+1}$. [Assuming stationarity for these residuals seems more plausible than assuming this for the cpue data themselves, as implicit in the Babayan *et al.* time series approaches.]

(2) The procedures (specifically those based on the Deriso/Schnute-85 model) could be implemented using double precision arithmetic, which should improve the estimation [the non-linear minimisation algorithm is less likely to fail owing to numerical errors (such as under- or overflow)].

(3) All the procedures could be reformulated to incorporate some of the other minimisation criteria used in the literature.

(4) The Lleonart *et al.* model could be transformed into an observation error estimator in a slightly simpler manner than has been performed in this study, as follows:

$$(C/E)_{i+1}-\varepsilon_{i+1} = g[(C/E)_i-\varepsilon_i] + (1-g)G\{C_{i+1}/[(C/E)_{i+1}-\varepsilon_{i+1}]\} \quad (11.1)$$

The errors ε_i may be estimated using ε_{i-1} and solving equation (11.1) numerically. The series $\{\varepsilon_i\}$ may be started either by estimating ε_1 in the non-linear search, or making the assumption that $(C/E)_1 - \varepsilon_1 = \alpha$ (which is equivalent to assuming $y_1 = K$).

(5) Ludwig and Walters (1988) suggest a family of Ricker functional forms which perform very successfully (proving to be much more robust than Power functions) in their simulations. As many of them perform better than the Ricker procedure investigated here, they deserve more attention.

(6) The TLS method of Ludwig *et al.* (1988) deserves further investigation in the light of the results reported here. For example, the effect of varying λ (the ratio of process error variance to total variance) should be examined.

11.1(b) Variance estimation procedures

Several additions to the tests discussed here should be performed:

(1) The gaps in the testing scheme should be filled. For example, estimates of bias and discrepancy should be obtained for the three best variance estimation procedures in combination with the three best model estimation procedures [the Butterworth-Andrew (Schaefer form) $y_1 = K$ TLS estimator (BA-S-TK), the Schnute-77(2) $y_1 = K$ observation error estimator (S72-S-OK) and the Schnute-77 $(C/E)_1 = qK$ process error estimator (S7-S-PFS)].

(2) (Conditioned) parametric bootstrap methods based on process error estimators (such as the method outlined in Chapter 10) should be investigated.

(3) Serial correlation effects could (perhaps) be incorporated into a (conditioned) parametric bootstrap, with the serial correlation coefficient estimated from the time series of residuals for the fit to the cpue data.

11.1(c) Extension of the scope of the robustness tests

In order to improve the realism of the Butterworth age-structured operating model and to determine how general the results obtained are, a number of modifications could be incorporated into the Butterworth age-structured operating model:

(1) Allowing the rate of natural mortality, M, to depend on both age and time, by making it a function of the number of adults at any time, will incorporate the effect of cannibalism.

(2) Environmental variables could be incorporated, as a multiplicative factor, into the noise term in the recruitment function :

$$N_{y,0} = e^{e_y+\varepsilon_y}\alpha B_y^s[\alpha\beta + B_y^s]^{-\gamma} \tag{11.2}$$

where e_y is the value of the (transformed) environmental value in year y. If the values of the environmental variables vary randomly from one year to the next, this amounts to no more than a contribution to the process error variance. It is likely, however, that the pertinent environmental variables may be serially correlated, so that this could be studied by changing the error distribution of ε_y to incorporate serial correlation.

(3) The catchability coefficient, q, could be defined as a function of time in order to reflect changes in efficiency and fleet composition.

(4) Selectivity, which in Appendix 7.A is assumed to be dependent on age alone, could likewise be defined as a function of time, thus allowing for the effects of changes in selectivity due, *inter alia*, to changes in mesh size.

(5) The two major hake species could be modelled separately (the Butterworth age-structured operating model ignores their differences, treating the two as a single species); the catch-effort statistics could then be computed from some combination of the statistics for each individual species. This could be of importance because Payne *et al.* (1988) report that recruitment of the two species shows different trends in recent years. In addition, the operating model could be altered to allow for sexual differences in natural mortality (see Andrew 1986), and even to represent different sub-areas exploited to differing degrees and interacting with each other through emigration and immigration.

(6) As cpue is unlikely to be exactly linearly related to biomass (due possibly to one of the factors listed in Chapter 3), it could perhaps be modelled more realistically by means of a power relationship (Cooke 1983) :

$$(C/E)_i = q(y_i)^p e^{\varepsilon_i} \qquad (11.3)$$

Further, as noted by Butterworth (1988c), in the first two years of the series in all Divisions of the ICSEAF Convention Area, the cpue values are much larger than the model fits suggest (possibly the result of first fishing down small high density regions); ensuring positive residuals in equation (11.3) for the first few years when generating artificial catch-effort data sets would be a way of modelling this effect.

(7) The multi-fleet nature of the hake fishery could be modelled by allowing a number of fleets to "fish" the resource, with each of these fleets having a different selectivity function and preferred area.

(8) Error distributions other than the log-normal could be used in the operating model.

(9) Different stocks could be investigated by varying the length of the data series, the rate of growth of individual fish, the exploitation history and the years in which catch and effort data first become available. Investigations by Punt and Butterworth (1988) suggest that the performance of estimation procedures varies substantially depending on these factors.

Serious problems with certain of these extensions exist, however, as it may not be possible (given the available data) to place reasonable bounds on the values of a number of the parameters and functional relationships required. It is unreasonable to expect any model estimation procedure to be robust in the face of an unboundedly wide spectrum of possible underlying structures.

11.1(d) Other aspects requiring attention

(1) The model selection procedure could be extended so that the quotas for year (n+2) rather than year (n+1) are estimated, with perhaps only the total catch for year (n+1) known (or

intelligently guessed). This is the practical situation in which quota estimation takes place at ICSEAF, with data for the current year usually not being available.

(2) Power factors have been suggested as an area of current concern because, if these are not correctly assigned, effort and hence trends in cpue could be severely biased (Butterworth 1988a). The extent to which errors in the estimation of power factors may bias these estimates could be investigated by incorporating them into the age-structured operating model.

(3) The performance of an estimation procedure could be evaluated, not in respect of the size of the discrepancy of each management variable, but rather in terms of the total catch made over a long period when the estimation procedure under consideration is used to assess the stock and to set quotas (without, of course, seriously depleting the resource). Results of similar analyses have been reported by Ludwig and Walters (1988).

11.2 Widening the scope of the tests performed

The testing procedure described in Chapter 7 may be extended so that estimation procedures based on data other than catch-effort data alone can be assessed. The amount of data generated by the Butterworth age-structured operating model may be increased to allow such procedures to be assessed using the techniques described in this study. This may be achieved in several ways :

(1) By generation of biomass survey data :

$$B_y^s = \sum_{a=0}^{9} S_a . w_a . N_{y,a} + \epsilon_y \qquad \text{with} \quad \epsilon_y \sim N(0,\sigma_B^2) \quad (11.4)$$

for use by procedures such as that of Andrew and Butterworth (1989), which require such data in addition to standard catch-effort data to estimate the parameters of the Butterworth-Andrew model.

(2) By generation of catch in numbers at age :

$$C_{y,a}^n = N_{y,a} . S_a . F_y [1 - \exp(-Z_{y,a})]/Z_{y,a} + \eta_{y,a} \qquad (11.5)$$

where $\eta_{y,a}$ is some appropriate error structure and $\Sigma (w_{a+1/2}) C_{y,a}^n = C_y$, for use by procedures such as VPA.

(3) By generation of recruitment survey data using the method in (2) for use by procedures such as those outlined in Butterworth (1988a).

12 CONCLUSIONS

12.1 Management variable estimation procedures

12.1(a) The model estimation procedures currently used by ICSEAF

Use of the Butterworth age-structured operating model indicates that all three of the procedures currently used by ICSEAF as the basis for the management of the hake resources in the ICSEAF Convention Area produce positively biased $Q_{0.1}$ estimates, and that these biases are often of substantial size, ranging from 21.5 to 70.9 percent. Their continued implementation is likely to lead to biological overexploitation of the resource, although the extent of this overexploitation is procedure-dependent, and worst for the Babayan *et al.* procedure (Bn-F-GLU). Of these procedures, the Butterworth-Andrew (Fox form) y_1 = K observation error estimator (BA-F-OK) appears to perform best.

The Babayan *et al.* time series methods are, as surmised by Butterworth and Andrew (1987a), very highly biased and not appropriate for use in the management of the hake stocks off southern Africa. This is because they use Gulland's regression method to estimate the target effort; this method is shown here (and in previous studies) to be biased in many situations (often severely positively so). It is also because they use a short data series (as few as six points in some cases) to estimate cpue in the forthcoming year, which results in estimates of quotas having much higher variance than estimates of the production model parameters. These techniques should thus be rejected as methods of providing the basis for annual catch quotas for ICSEAF.

12.1(b) The "best" model estimation procedures

Many of the 106 model estimation procedures investigated provide estimates of management variables which are substantially positively biased and none is able either to reproduce the "true" biomass trend exactly or to estimate accurately, over its entire range, the "true" (equilibrium) surplus production curve underlying the operating model. This suggests that production-model-type estimation procedures alone may not be adequate for management of the ICSEAF hake resources and that there may be scope for approaches making direct use of age composition data (e.g. VPA linked to yield-per-recruit analysis). Nevertheless, some of the procedures [specifically the six selected here: the Butterworth-Andrew (Schaefer form) $y_1 = K$ observation error estimator (BA-S-OK), the Butterworth-Andrew (Schaefer form) $y_1 = K$ TLS estimator (BA-S-TK), the Schnute-77(1) (S71-S-OK) and Schnute-77(2) (S72-S-OK) $y_1 = K$ observation error estimators, the Schnute-77 $(C/E)_1 = qK$ (with smoothed cpue data) process error estimator (S7-S-PFS) and the Lleonart *et al.* (Fox form) Linear Method (using smoothed cpue data) process error estimator (Ll-F-PLS)] perform relatively well, each producing a discrepancy of approximately 20%, on average, for $Q_{0.1}$. Thus it would appear that a place still remains for production model assessment procedures in the management of the ICSEAF hake stocks.

Although in this study six procedures have been selected on the basis of their performance in the simulation trials, it would not be prudent to advocate any single procedure as the "best", to be adopted finally by ICSEAF, firstly because the Butterworth age-structured operating model used does not necessarily constitute the best possible representation of a typical hake stock in any of the ICSEAF Divisions, and further because conceivably more stringent robustness tests need to be carried out prior to final conclusions being drawn. (Some suggestions for extensions to the Butterworth age-structured operating model are made in Chapter 11.)

12.1(d) Other aspects

When the Butterworth age-structured operating model is used to generate artificial data sets for three extreme error combinations, several classes of production-model-type estimation procedures (the Babayan *et al.* time series methods, the Shepherd procedures, all observation error estimators which estimate y_1 and all process error estimators which estimate α) are found to be very badly biased and therefore seem inappropriate for use in the management of the hake stocks off southern Africa. Pre-smoothing of the cpue data does not appear to improve accuracy and precision substantially.

The reason for the failure of the Deriso/Schnute-85 procedures here is that the minimisation algorithm used to estimate the parameters has difficulty finding a minimum. In addition, the model underlying these procedures, owing to its assumption of an infinite number of year classes, is unable to model adequately a situation in which natural mortality is essentially infinite after some age. Further investigation using different minimisation routines and greater arithmetic precision in the computations is necessary before final conclusions can be drawn about the usefulness of these procedures.

After performing a number of robustness tests (by varying the parameters of the Butterworth age-structured operating model), several other classes of procedures based on the Fox form of the surplus production function were rejected. In general, the Schaefer form of the surplus production function appears to be more robust to the operating model structure than is the Fox form (or certain others also investigated, including the Ricker form). Additional robustness tests (some of which are outlined in Chapter 11) are necessary to allow further examination of the behaviour of the different model estimation procedures in more extreme (and possibly more realistic) situations, *inter alia* to investigate the generality of the above conclusion.

The "serial correlation" effect (caused by using the same model estimation procedure both to assess the stock and thereafter to set quotas) does not appear to bias management variable estimates substantially.

The current level of contrast in the data investigated (typical of hake in Divisions 1.3 + 1.4) is such that neither the observation error estimators nor the process error estimators are able to estimate all their parameters [minimally four - see Section 10.1(e)] adequately, so that some auxiliary information is required to obtain accurate and precise estimates of management variables. The use of auxiliary information to fix (or at least place bounds on) the stock size prior to exploitation, in the case of observation error estimators, or the corresponding cpue value (in terms of the model parameters K and/or q), in the case of process error estimators, is shown to improve management variable estimation substantially. Neglect of such auxiliary information can probably explain the poor performance of the Lleonart *et al.* (q estimated) (using unsmoothed cpue data) process error estimator (Ll-F-PEU) in these simulations. The level of data contrast is shown to be critical to the precision with which parameters can be estimated, and therefore additional robustness tests in which the length of the data series is altered should be performed if these studies are to be pursued further.

12.2 Variance estimation procedures

The investigations have shown that all of the 10 variance estimation procedures considered provide estimates which are biased to some extent (nearly all negatively). The "naive" and *ad hoc* bootstraps perform poorly, in all likelihood because they do not take the regression-like nature of the estimation into account. They are thus inappropriate for use with production-model-like estimation procedures and any results generated using them should be rejected.

The biases that result from use of the different variance estimation procedures are critically dependent on whether the correct error structure (i.e. the structure which most closely approximates the "true" underlying error structure of the operating model being used) is assumed for the model estimation procedure. In addition, although the biases for most of the variance estimation procedures investigated are comparable for the various model estimation procedures considered (given a fixed operating model error structure), this is not the case for the jack-knife method in conjunction with the original Lleonart *et* *al*. procedure (Ll-F-PEU). (Unlike the other model estimation procedures considered, the bias of the Ll-F-PEU procedure with this variance estimation procedure is positive.)

The "serial correlation" effect raised by Butterworth (1988a) appears to be insubstantial in comparison to the other biases inherent in variance estimation.

The variance estimation procedure recommended on the basis of these results (in the context of using an inverse variance weighted average of management variable estimates provided by different model estimation procedures, which is to be the procedure employed by ICSEAF) is the (conditioned) parametric bootstrap. Although the jack-knife procedure could also be considered, its use would require the calculation of (differential) bias correction factors for variance estimates in order to produce values which are unbiased relative to each other when using the Lleonart *et al.* (Fox form) (q estimated) (with unsmoothed cpue data) process error estimator (Ll-F-PEU) (and probably also the Ll-S-PEU estimator). This would be problematic, as the bias of this estimator relative to that of others varies markedly according to the error structure of the operating model.

As confidence intervals for the estimates of management variables (and parameters) are likely to be asymmetrical, methods for their estimation which take this possibility into account should be used. The bias-corrected percentile method is recommended on the basis of its performance in the simulations, and because it is the most theoretically defensible method of confidence interval estimation tested here. (Standard intervals must be employed when using the jack-knife method, however, as the bias-corrected percentile method requires the use of a bootstrap technique.) This study has shown that the size of the confidence intervals is likely to be negatively biased, the extent of this bias depending on the error structure of the operating model.

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APPENDICES

In order to simplify the presentation of the results, the names of the model estimation procedures have been replaced by acronyms, in some of the Tables in these Appendices. Each of these acronyms is constructed from distinct mnemonics, separated by dashes, representing :

1) the model upon which the estimation procedure is based,
2) the form of the surplus production function used and
3) the method used to estimate the model parameters.

The acronym BA-F-OK, for example, represents the Butterworth-Andrew (Fox form) $y_1 = K$ observation error estimator.

The following mnemonics are used to represent the different models (part 1 of each acronym) :

Butterworth-Andrew	- BA
Babayan *et al.*	- Bn
Babayan-Kizner	- BK
Horbowy-Draganik	- HD
Lleonart *et al.*	- Ll
Shepherd	- Sh
Schnute-77(1)	- S71
Schnute-77(2)	- S72
Schnute-77 (process error form)	- S7
Schnute-85	- S8

The second mnemonic reflects the particular form of the surplus production function used :

Beverton-Holt	- B
Fox	- F
Pella-Tomlinson	- PT
Power	- Po
Ricker	- R
Schaefer	- S

and the third mnemonic, the method of parameter estimation. This last mnemonic can itself be divided into three parts, representing the error structure assumed (observation/process - O/P), the assumptions made about the model parameters, and whether or not the cpue data are pre-smoothed (smoothed/unsmoothed - S/U). [Note that ℓn(cpue) minimisation has been used throughout this thesis, so that no distinction for different minimisation criteria is indicated.] As the cpue data have been smoothed only for process error estimators and for procedures based on Gulland's regression method, the last part of the third mnemonic is omitted for all except such cases. The third mnemonic is thus constructed as follows:

1) For Observation error estimators:

a) $y_1 = K$ - OK
b) y_1 Estimated - OE

2) For TLS estimators (observation and process error assumed to have equal variance):

a) $y_1 = K$ - TK

b) y_1 Estimated - TE

3) For Process error estimators:

a) α is Estimated (Smoothed cpue) - PES

b) α is set equal to First cpue value (Smoothed cpue) - PFS

c) α is estimated by the Linear Method (Smoothed cpue) - PLS

d) α is Estimated (Unsmoothed cpue) - PEU

e) α is set equal to First cpue value (Unsmoothed cpue) - PFU

f) α is estimated by the Linear Method (Unsmoothed cpue) - PLU

4) For use with the Gulland procedure:

a) Adaptive Lag 0 method (Unsmoothed cpue) - G0U

b) Adaptive Lag 1 method (Unsmoothed cpue) - G1U

c) ARIMA method (Unsmoothed cpue) - GAU

d) Combined Brown method (Unsmoothed cpue) - GBU

e) EXponential Smoothing method (Unsmoothed cpue) - GXU

f) Linear method (Unsmoothed cpue) - GLU

g) Maximum Entropy method (Unsmoothed cpue) - GMU

h) Adaptive Lag 0 method (Smoothed cpue) - G0S

i) Adaptive Lag 1 method (Smoothed cpue) - G1S

j) ARIMA method (Smoothed cpue) - GAS

k) Combined Brown method (Smoothed cpue) - GBS

l) EXponential Smoothing method (Smoothed cpue) - GXS

m) Linear method (Smoothed cpue) - GLS

n) Maximum Entropy method (Smoothed cpue) - GMS

In the following Tables the following symbols are used:

+ not significantly different from zero at the 5% level

* bias (or discrepancy) larger than 1000%

?? one of the simulations resulted in an error (e.g. taking the logarithm of a negative number or attempting to invert a near singular matrix)

Appendix A: Butterworth age-structured operating model with observation error only: estimates of the percentage bias in the estimates of the variables and parameters used in the management of the ICSEAF hake stocks. The standard error of the percentage bias estimate is given in parenthesis. The operating model used to generate the artificial data is described in Appendix 7.A. All artificial data sets used in the estimation of the biases are generated using $\sigma_q = 0.13$ and $\sigma_r = 0$. Tables (1) to (12) below contain the results of the following simulations :

Table	Details of estimation procedures used
1	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)
2	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)
3	Babayan-Kizner procedure (Fox and Schaefer forms)
4	Butterworth-Andrew procedure (Fox form)
5	Butterworth-Andrew procedure (Schaefer form)
6	Horbowy-Draganik procedure (Pella-Tomlinson model)
7	Lleonart *et al.* procedure (Fox form)
8	Lleonart *et al.* procedure (Schaefer form)
9	Schnute-77 procedure (based on the Schaefer model)
10	Shepherd procedure
11	Schnute-85 procedure (Fox form)
12	TLS based procedures

Appendix A(1): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Linear Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	56.99 (10.86)	32.45 (0.93)	47.65 (1.36)
Brown Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	24.50 (2.28)	32.45 (0.93)	17.09 (2.14)
Maximum Entropy Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	45.64 (2.02)	32.45 (0.93)	36.97 (1.90)
ARIMA Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	706.05 (148.72)	32.45 (0.93)	658.08 (167.08)
Exponential Smoothing Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	29.89 (3.08)	32.45 (0.93)	22.16 (2.90)
Adaptive (Lag 0) Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	39.14 (5.30)	32.45 (0.93)	30.86 (4.99)
Adaptive (Lag 1) Unsmoothed cpue data	38.54 (0.97)	26.63 (0.38)	43.92 (2.20)	32.45 (0.93)	35.36 (2.07)
Linear Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	68.02 (1.53)	42.48 (1.00)	58.02 (1.44)
Brown Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	51.22 (1.84)	42.48 (1.00)	42.22 (1.74)
Maximum Entropy Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	57.67 (1.80)	42.48 (1.00)	48.29 (1.69)
ARIMA Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	115.84 (91.00)+	42.48 (1.00)	103.00 (85.58)+
Exponential Smoothing Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	55.52 (1.59)	42.48 (1.00)	46.26 (1.49)
Adaptive (Lag 0) Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	54.87 (1.76)	42.48 (1.00)	45.65 (1.66)
Adaptive (Lag 1) Smoothed cpue data	49.03 (1.04)	30.56 (0.43)	55.91 (1.78)	42.48 (1.00)	46.63 (1.67)

Appendix A(2): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Linear * Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	20.31 (0.95)	16.87 (0.60)	30.31 (1.03)
Brown Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	-4.71 (1.68)	16.87 (0.60)	3.21 (1.82)+
Maximum Entropy Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	11.50 (1.44)	16.87 (0.60)	20.87 (1.56)
ARIMA Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	483.26 (137.65)	16.87 (0.60)	531.73 (162.23)
Exponential Smoothing Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	-0.46 (2.33)+	16.87 (0.60)	7.81 (2.52)
Adaptive (Lag 0) Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	6.63 (4.05)+	16.87 (0.60)	15.49 (4.39)
Adaptive (Lag 1) Unsmoothed cpue data	6.14 (0.54)	23.12 (0.23)	10.35 (1.61)	16.87 (0.60)	19.52 (1.74)
Linear Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	23.54 (0.98)	20.61 (0.61)	33.81 (1.06)
Brown Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	11.15 (1.24)	20.61 (0.61)	20.34 (1.35)
Maximum Entropy Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	15.92 (1.21)	20.61 (0.61)	25.55 (1.31)
ARIMA Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	60.16 (66.67)+	20.61 (0.61)	73.47 (72.21)+
Exponential Smoothing Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	14.36 (1.05)	20.61 (0.61)	23.86 (1.14)
Adaptive (Lag 0) Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	13.86 (1.17)	20.61 (0.61)	23.32 (1.27)
Adaptive (Lag 1) Smoothed cpue data	9.54 (0.56)	23.72 (0.26)	14.62 (1.19)	20.61 (0.61)	24.15 (1.29)

Appendix A(3): Babayan-Kizner procedure (Fox and Schaefer forms)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Unsmoothed cpue data q estimated (Fox)	20.41 (2.85)	18.42 (1.55)	18.66 (2.86)	32.58 (3.14)	28.53 (3.10)
Unsmoothed cpue data $(C/E)_1$ = qK (Fox)	22.68 (1.51)	13.07 (0.68)	109.24 (3.01)	17.29 (1.44)	96.79 (2.83)
Unsmoothed cpue data Linear method (Fox)	15.27 (1.21)	10.76 (0.59)	97.85 (2.67)	10.21 (1.16)	86.07 (2.51)
Smoothed cpue data q estimated (Fox)	69.98 (3.38)	25.91 (1.33)	156.71 (3.72)	62.52 (3.23)	141.43 (3.50)
Smoothed cpue data $(C/E)_1$ = qK (Fox)	17.92 (1.12)	7.89 (0.57)	92.06 (2.30)	12.74 (1.07)	80.63 (2.17)
Smoothed cpue data Linear method (Fox)	11.44 (1.07)	5.94 (0.55)	81.93 (2.23)	6.55 (1.02)	71.10 (2.10)
Unsmoothed cpue data q estimated (Sch.)	113.00 (8.01)	46.77 (3.41)	217.61 (25.50)	103.64 (7.66)	198.71 (7.56)
Unsmoothed cpue data $(C/E)_1$ = qK (Sch.)	-15.73 (0.88)	5.97 (0.56)	-17.74 (1.12)	-7.21 (0.97)	-10.90 (1.21)
Unsmoothed cpue data Linear method (Sch.)	-19.53 (0.73)	5.36 (0.53)	-21.56 (1.02)	-11.40 (0.81)	-15.04 (1.10)
Smoothed cpue data q estimated (Sch.)	2.54 (1.16)	6.71 (0.60)	1.08 (1.32)+	12.90 (1.29)	9.48 (1.43)
Smoothed cpue data $(C/E)_1$ = qK (Sch.)	-18.57 (0.64)	1.51 (0.49)	-20.20 (0.93)	-10.34 (0.71)	-13.57 (1.01)
Smoothed cpue data Linear method (Sch.)	-22.13 (0.62)	0.87 (0.47)+	-23.74 (0.90)	-14.25 (0.69)	-17.40 (0.97)

Appendix A(4): Butterworth-Andrew procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error y_1 = K	19.15 (0.69)	8.31 (0.43)	29.16 (1.06)	13.92 (0.66)	21.48 (1.00)
Observation Error y_1 estimated	39.95 (2.34)	15.63 (0.86)	48.51 (2.29)	33.80 (2.23)	39.68 (2.15)
Process Error Unsmoothed cpue data q estimated	436.86 (91.21)	209.43 (44.31)	458.24 (92.67)	413.28 (87.21)	425.02 (87.47)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	46.71 (2.07)	34.97 (1.09)	61.89 (2.78)	40.27 (1.98)	52.25 (2.62)
Process Error Unsmoothed cpue data Linear method	37.37 (1.66)	31.85 (1.00)	51.91 (2.42)	31.33 (1.59)	42.87 (2.27)
Process Error Smoothed cpue data q estimated	93.05 (3.69)	37.70 (1.49)	102.63 (3.63)	84.57 (3.53)	90.57 (3.41)
Process Error Smoothed cpue data $(C/E)_1$ = qK	24.18 (1.24)	13.53 (0.65)	33.19 (1.80)	18.73 (1.19)	25.27 (1.69)
Process Error Smoothed cpue data Linear method	17.03 (1.18)	11.16 (0.62)	25.58 (1.71)	11.89 (1.13)	18.11 (1.61)

Appendix A(5): Butterworth-Andrew procedure (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error y_1 = K	-15.06 (0.42)	3.49 (0.38)	-6.14 (0.77)	-6.47 (0.46)	1.66 (0.83)
Observation Error y_1 estimated	-6.42 (0.82)	5.46 (0.42)	1.46 (0.94)+	3.04 (0.91)	9.89 (1.02)
Process Error Unsmoothed cpue data q estimated	344.28 (94.94)	235.67 (61.26)	362.77 (94.59)	389.18 (104.54)	401.24 (102.45)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	2.18 (2.38)+	28.04 (2.82)	12.87 (2.74)	12.50 (2.62)	22.25 (2.97)
Process Error Unsmoothed cpue data Linear method	-4.70 (1.16)	24.42 (0.65)	5.53 (1.76)	4.93 (1.28)	14.31 (1.91)
Process Error Smoothed cpue data q estimated	12.71 (1.30)	13.39 (0.69)	19.52 (1.49)	24.10 (1.43)	29.45 (1.62)
Process Error Smoothed cpue data $(C/E)_1$ = qK	-15.11 (0.75)	5.71 (0.56)	-8.59 (1.18)	-6.53 (0.82)	-0.99 (1.28)+
Process Error Smoothed cpue data Linear method	-19.28 (0.73)	4.42 (0.57)	-13.11 (1.16)	-11.13 (0.81)	-5.88 (1.25)

Appendix A(6): Horbowy-Draganik procedure (Pella-Tomlinson model)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	20.43 (0.72)	11.81 (0.47)	33.37 (1.11)	2.64 (0.62)	11.83 (0.93)
Observation Error y_1 estimated	45.20 (2.89)	20.76 (1.11)	56.91 (1.11)	24.19 (2.47)	32.01 (2.38)
Process Error Unsmoothed cpue data q estimated	576.98 (102.63)	276.97 (50.17)	627.56 (113.79)	476.81 (87.32)	509.71 (95.24)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	42.39 (2.01)	31.40 (1.06)	56.83 (2.71)	21.22 (1.72)	31.34 (2.27)
Process Error Unsmoothed cpue data Linear method	33.76 (1.75)	28.58 (1.09)	47.28 (2.44)	13.76 (1.49)	23.22 (2.05)
Process Error Smoothed cpue data q estimated	91.79 (3.99)	36.33 (1.64)	101.03 (3.90)	63.07 (3.39)	68.14 (3.26)
Process Error Smoothed cpue data $(C/E)_1 = qK$	21.64 (1.23)	11.42 (0.65)	30.28 (1.76)	3.41 (1.04)	8.96 (1.47)
Process Error Smoothed cpue data Linear method	14.74 (1.16)	9.39 (0.60)	23.01 (1.67)	-2.22 (0.99)	3.12 (1.40)

Appendix A(7): Lleonart *et al.* procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	-7.85 (0.71)	-11.11 (0.41)	-6.84 (0.97)	-11.89 (0.68)	-12.39 (0.91)
Observation Error y_1 estimated	5.24 (3.25)+	7.84 (5.47)+	6.34 (3.16)	0.62 (3.11)+	0.01 (2.97)+
Process Error Unsmoothed cpue data q estimated	62.14 (3.68)	32.80 (2.05)	40.13 (2.61)	55.02 (3.51)	40.34 (2.61)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	21.76 (1.62)	12.01 (0.72)	13.23 (1.47)	16.41 (1.54)	13.07 (1.45)
Process Error Unsmoothed cpue data Linear method	13.95 (1.25)	9.36 (0.59)	7.56 (1.27)	8.94 (1.20)	7.42 (1.26)
Process Error Smoothed cpue data q estimated	38.79 (3.46)	11.05 (1.31)	31.55 (2.92)	32.70 (3.30)	27.88 (2.83)
Process Error Smoothed cpue data $(C/E)_1 = qK$	7.36 (1.12)	-1.89 (0.78)	5.79 (1.33)	2.65 (1.06)	2.77 (1.28)
Process Error Smoothed cpue data Linear method	-21.14 (0.57)	2.30 (0.47)	-27.80 (0.71)	-13.17 (0.63)	-21.80 (0.77)

Appendix A(8): Lleonart *et al.* procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	-19.85 (0.40)	-4.02 (0.41)	-14.51 (0.73)	-11.75 (0.44)	-7.40 (0.79)
Observation Error y_1 estimated	*	*	*	*	*
Process Error Unsmoothed cpue data q estimated	32.79 (1.97)	27.07 (1.05)	-13.70 (1.19)	46.21 (2.16)	-6.51 (1.29)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	-7.27 (0.80)	17.02 (0.49)	-27.83 (0.77)	2.10 (0.88)	-21.82 (0.83)
Process Error Unsmoothed cpue data Linear method	-10.99 (0.64)	16.59 (0.48)	-29.15 (0.74)	-2.01 (0.71)	-23.25 (0.80)
Process Error Smoothed cpue data q estimated	18.98 (1.83)	12.46 (0.93)	-2.12 (1.33)+	30.99 (2.02)	6.03 (1.44)
Process Error Smoothed cpue data $(C/E)_1 = qK$	-18.03 (0.59)	2.31 (0.47)	-25.76 (0.73)	-9.75 (0.65)	-19.58 (0.79)
Process Error Smoothed cpue data Linear method	1.26 (1.06)+	-3.87 (0.56)	0.48 (1.27)+	-3.19 (1.02)	-2.40 (1.28)+

Appendix A(9): Schnute-77 procedure (based on the Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error (1) $y_1 = K$	-12.41 (0.45)	5.16 (0.41)	-3.14 (0.79)	-3.56 (0.49)	4.91 (0.86)
Observation Error (1) y_1 estimated	-1.36 (1.09)	7.61 (0.56)	6.68 (1.22)	8.60 (1.21)	15.55 (1.32)
Observation Error (2) $y_1 = K$	-14.43 (0.43)	2.96 (0.39)	-5.57 (0.78)	-5.78 (0.47)	2.28 (0.84)
Observation Error (2) y_1 estimated	-2.10 (0.96)	6.21 (0.49)	5.52 (1.08)	7.79 (1.06)	14.30 (1.17)
Process Error Unsmoothed cpue data q estimated	23.01 (1.44)	27.22 (0.79)	33.81 (1.65)	35.44 (1.60)	44.93 (1.78)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	-5.38 (0.93)	19.06 (0.48)	4.80 (1.24)	4.17 (1.02)	13.51 (1.34)
Process Error Unsmoothed cpue data Linear method	-9.69 (0.73)	18.33 (0.44)	4.06 (1.13)	-0.57 (0.81)+	8.75 (1.19)
Process Error Smoothed cpue data q estimated	-1.85 (1.01)+	7.70 (0.52)	4.40 (1.15)	8.07 (1.11)	13.08 (1.24)
Process Error Smoothed cpue data $(C/E)_1 = qK$	-16.22 (0.63)	4.46 (0.44)	-10.13 (0.94)	-7.75 (0.69)	-2.66 (1.02)
Process Error Smoothed cpue data Linear method	-19.58 (0.61)	4.19 (0.42)	-13.66 (0.91)	-11.46 (0.67)	-6.49 (0.98)

Appendix A(10): Shepherd procedure

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	19.84 (1.23)	9.18 (0.58)	30.38 (1.79)	16.32 (0.92)	24.23 (1.35)
Observation Error y_1 estimated	99.61 (25.89)	24.26 (2.82)	110.72 (25.86)	53.69 (6.27)	59.57 (6.26)
Process Error Unsmoothed cpue data q estimated	364.22 (29.48)	69.73 (2.94)	416.56 (33.99)	102.44 (5.06)	120.31 (5.82)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	*	575.77 (101.57)	*	*	*
Process Error Unsmoothed cpue data Linear method	??	??	??	??	??
Process Error Smoothed cpue data q estimated	174.00 (12.93)	59.69 (2.94)	186.04 (13.70)	136.32 (6.97)	142.05 (6.80)
Process Error Smoothed cpue data $(C/E)_1 = qK$	26.74 (2.13)	16.44 (0.86)	35.65 (2.62)	23.17 (1.68)	29.50 (2.07)
Process Error Smoothed cpue data Linear method	??	??	??	??	??

Appendix A(11): Schnute-85 procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	-12.37 (0.16)	-17.70 (0.00)	-22.10 (0.00)	-14.96 (0.16)	-25.63 (0.00)
Observation Error y_1 estimated	-97.49 (0.00)!	-37.19 (0.00)!	-98.58 (0.00)!	-97.56 (0.00)!	-98.64 (0.00)!

Note: ! See discussion in Chapter 10

Appendix A(12): TLS based procedures

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Butterworth-Andrew (Schaefer form) $y_1 = K$	-17.05 (0.50)	4.52 (0.41)	-11.80 (0.89)	-8.67 (0.56)	-4.47 (0.97)
Butterworth-Andrew (Schaefer form) y_1 estimated	-7.83 (0.89)	7.06 (0.47)	-2.46 (1.09)	1.49 (0.97)	5.65 (1.18)
Butterworth-Andrew (Fox form) $y_1 = K$	16.93 (0.90)	9.05 (0.48)	23.74 (1.36)	11.79 (0.86)	16.38 (1.28)
Butterworth-Andrew (Fox form) y_1 estimated	39.70 (3.15)	17.55 (1.24)	46.25 (2.99)	33.57 (3.01)	37.55 (2.81)
Ricker Model $y_1 = K$	-5.03 (1.02)	8.25 (0.54)	5.99 (1.16)	5.85 (1.13)	16.24 (1.27)
Power Model $y_1 = K$	77.98 (9.50)	37.33 (6.17)	94.75 (9.84)	70.11 (9.08)	83.10 (9.26)

Appendix B: Butterworth age-structured operating model with mixed error: as for Appendix A except that all artificial data sets used in the estimation of the biases are generated using $\sigma_q = 0.1$ and $\sigma_r = 0.2$. Tables (1) to (12) below contain the results of the following simulations :

Table	Details of estimation procedures used
1	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)
2	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)
3	Babayan-Kizner procedure (Fox and Schaefer forms)
4	Butterworth-Andrew procedure (Fox form)
5	Butterworth-Andrew procedure (Schaefer form)
6	Horbowy-Draganik procedure (Pella-Tomlinson model)
7	Lleonart *et al.* procedure (Fox form)
8	Lleonart *et al.* procedure (Schaefer form)
9	Schnute-77 procedure (based on the Schaefer model)
10	Shepherd procedure
11	Schnute-85 procedure (Fox form)
12	TLS based procedures

Appendix B(1): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Linear Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	65.69 (2.14)	40.05 (1.46)	55.83 (2.01)
Brown Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	34.27 (2.53)	40.05 (1.46)	26.28 (2.38)
Maximum Entropy Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	53.27 (2.41)	40.05 (1.46)	44.15 (2.67)
ARIMA Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	56.33 (141.53)+	40.05 (1.46)	47.04 (133.11)+
Exponential Smoothing Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	40.80 (3.07)	40.05 (1.46)	32.40 (2.88)
Adaptive (Lag 0) Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	68.20 (10.30)	40.05 (1.46)	58.21 (9.69)
Adaptive (Lag 1) Unsmoothed cpue data	46.49 (1.52)	32.89 (0.93)	51.53 (2.47)	40.05 (1.46)	42.57 (2.32)
Linear Smoothed cpue data	56.44 (1.88)	37.49 (1.18)	76.22 (1.22)	49.57 (1.79)	65.73 (2.39)
Brown Smoothed cpue data	56.44 (1.88)	37.49 (1.18)	61.23 (2.44)	49.57 (1.79)	51.56 (2.30)
Maximum Entropy Smoothed cpue data	56.44 (1.88)	37.96 (1.18)	64.36 (2.48)	49.57 (1.79)	54.58 (2.34)
ARIMA Smoothed cpue data	56.44 (1.88)	37.96 (1.18)	-20.86 (19.80)+	49.57 (1.79)	-14.28 (21.45)+
Exponential Smoothing Smoothed cpue data	56.44 (1.88)	37.96 (1.18)	63.39 (4.05)	49.57 (1.79)	53.67 (2.23)
Adaptive (Lag 0) Smoothed cpue data	56.44 (1.88)	37.96 (1.18)	62.58 (2.37)	49.57 (1.79)	52.80 (2.17)
Adaptive (Lag 1) Smoothed cpue data	56.44 (1.88)	37.96 (1.18)	62.98 (2.36)	49.57 (1.79)	53.31 (2.22)

Appendix B(2): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Linear Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	24.34 (1.22)	21.12 (0.80)	34.68 (1.32)
Brown Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	0.48 (1.60)+	21.12 (0.80)	8.83 (1.73)
Maximum Entropy Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	14.87 (1.47)	21.12 (0.80)	24.41 (1.59)
ARIMA Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	12.33 (112.40)+	21.12 (0.80)	21.88 (121.74)+
Exponential Smoothing Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	5.70 (2.07)	21.12 (0.80)	14.48 (2.24)
Adaptive (Lag 0) Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	26.63 (7.99)	21.12 (0.80)	37.23 (8.66)
Adaptive (Lag 1) Unsmoothed cpue data	10.01 (0.73)	27.15 (0.53)	13.88 (1.57)	21.12 (0.80)	23.39 (14.31)+
Linear Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	28.87 (1.36)	25.11 (0.93)	38.50 (1.47)
Brown Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	16.90 (1.34)	25.11 (0.93)	26.77 (1.46)
Maximum Entropy Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	19.22 (1.32)	25.11 (0.93)	29.13 (1.43)
ARIMA Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	10.22 (25.86)+	25.11 (0.93)	3.66 (24.33)+
Exponential Smoothing Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	18.66 (1.26)	25.11 (0.93)	28.46 (1.36)
Adaptive (Lag 0) Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	17.95 (1.26)	25.11 (0.93)	27.74 (6.09)
Adaptive (Lag 1) Smoothed cpue data	13.63 (0.84)	28.73 (0.67)	18.39 (1.25)	25.11 (0.93)	28.25 (1.36)

Appendix B(3): Babayan-Kizner procedure (Fox and Schaefer forms)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Unsmoothed cpue data q estimated (Fox)	122.21 (23.42)	57.77 (11.11)	220.18 (21.50)	112.45 (22.39)	201.14 (20.22)
Unsmoothed cpue data $(C/E)_1$ = qK (Fox)	25.91 (1.51)	16.46 (1.07)	109.21 (2.99)	20.38 (1.44)	97.23 (2.81)
Unsmoothed cpue data Linear method (Fox)	18.43 (1.29)	13.83 (0.98)	98.32 (2.72)	13.23 (1.23)	86.52 (2.56)
Smoothed cpue data q estimated (Fox)	75.48 (4.47)	33.76 (2.43)	161.32 (5.34)	67.77 (4.28)	145.77 (5.02)
Smoothed cpue data $(C/E)_1$ = qK (Fox)	23.49 (1.35)	12.93 (1.06)	97.40 (2.62)	18.07 (1.28)	85.65 (2.46)
Smoothed cpue data Linear method (Fox)	16.17 (1.24)	10.36 (0.98)	86.42 (2.49)	11.07 (1.19)	75.32 (2.34)
Unsmoothed cpue data q estimated (Sch.)	22.51 (5.33)	24.56 (3.44)	20.96 (5.66)	34.89 (5.87)	31.02 (6.13)
Unsmoothed cpue data $(C/E)_1$ = qK (Sch.)	-13.98 (0.81)	8.39 (0.77)	-16.41 (1.03)	-5.29 (0.89)	-9.47 (1.12)
Unsmoothed cpue data Linear method (Sch.)	-18.01 (0.71)	7.29 (0.74)	-20.44 (0.93)	-9.73 (0.79)	-13.83 (1.00)
Smoothed cpue data q estimated (Sch.)	6.82 (1.71)	13.19 (1.35)	5.32 (1.91)	17.62 (1.88)	14.07 (2.07)
Smoothed cpue data $(C/E)_1$ = qK (Sch.)	-15.71 (0.72)	4.90 (0.78)	-17.63 (0.97)	-7.19 (0.80)	-10.78 (1.05)
Smoothed cpue data Linear method (Sch.)	-19.76 (0.69)	3.75 (0.76)	-21.66 (0.91)	-11.66 (0.76)	-15.15 (0.98)

Appendix B(4): Butterworth-Andrew procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error y_1 = K	25.01 (1.29)	13.86 (1.05)	34.96 (1.82)	19.52 (1.23)	26.93 (1.71)
Observation Error y_1 estimated	50.16 (4.59)	25.04 (2.24)	59.50 (4.71)	43.57 (4.39)	50.01 (4.43)
Process Error Unsmoothed cpue data q estimated	307.06 (63.22)	154.67 (32.09)	328.38 (67.51)	289.18 (60.44)	302.88 (63.49)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	44.28 (1.90)	33.22 (1.32)	56.50 (2.52)	37.94 (1.82)	47.19 (2.37)
Process Error Unsmoothed cpue data Linear method	35.28 (1.60)	29.86 (1.19)	46.93 (2.20)	29.33 (1.53)	38.19 (2.07)
Process Error Smoothed cpue data q estimated	95.20 (4.22)	44.10 (2.41)	104.62 (4.47)	86.62 (4.03)	92.45 (4.21)
Process Error Smoothed cpue data $(C/E)_1$ = qK	29.43 (1.42)	18.30 (1.09)	37.70 (1.90)	23.74 (1.36)	29.50 (1.78)
Process Error Smoothed cpue data Linear method	21.39 (1.32)	15.25 (1.03)	29.21 (1.75)	16.06 (1.27)	21.52 (1.65)

Appendix B(5): Butterworth-Andrew procedure (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error y_1 = K	-11.98 (0.70)	7.32 (0.75)	-3.19 (1.09)	-3.09 (0.77)	4.85 (1.19)
Observation Error y_1 estimated	-1.48 (1.57)	11.86 (1.07)	6.49 (1.74)	8.48 (1.72)	15.34 (1.89)
Process Error Unsmoothed cpue data q estimated	169.72 (46.96)	122.42 (28.34)	181.82 (47.15)	196.97 (51.70)	205.24 (51.07)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	-2.43 (1.18)	22.59 (1.15)	6.18 (1.63)	7.43 (1.30)	15.00 (1.76)
Process Error Unsmoothed cpue data Linear method	-7.63 (1.08)	20.62 (1.17)	0.60 (1.52)	1.69 (1.19)	8.96 (1.65)
Process Error Smoothed cpue data q estimated	15.73 (1.67)	19.22 (1.41)	22.13 (1.92)	27.42 (1.85)	32.28 (2.07)
Process Error Smoothed cpue data $(C/E)_1$ = qK	-12.44 (0.79)	8.90 (0.83)	-6.51 (1.13)	-3.59 (0.87)	1.26 (1.22)
Process Error Smoothed cpue data Linear method	-17.15 (0.76)	7.05 (0.81)	-11.56 (1.08)	-8.78 (0.84)	-4.21 (1.17)

Appendix B(6): Horbowy-Draganik procedure (Pella-Tomlinson model)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error y_1 = K	25.90 (1.26)	16.38 (10.51)+	38.00 (1.82)	7.48 (1.07)	15.91 (1.53)
Observation Error y_1 estimated	54.47 (4.80)	29.17 (2.39)	66.09 (4.99)	32.80 (4.13)	40.46 (4.22)
Process Error Unsmoothed cpue data q estimated	*	*	53.17 (508.73)+	*	*
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	39.61 (1.88)	29.06 (1.30)	51.13 (2.48)	18.62 (1.60)	26.31 (2.07)
Process Error Unsmoothed cpue data Linear method	31.40 (1.55)	26.49 (11.59)	42.44 (2.13)	11.83 (1.32)	19.25 (1.78)
Process Error Smoothed cpue data q estimated	92.81 (4.05)	41.91 (2.31)	102.18 (8.77)	63.97 (3.46)	69.13 (6.16)
Process Error Smoothed cpue data $(C/E)_1$ = qK	26.71 (1.36)	16.13 (1.05)	34.58 (1.81)	7.84 (1.15)	12.67 (1.52)
Process Error Smoothed cpue data Linear method	18.84 (1.28)	13.42 (1.00)	26.41 (1.71)	1.46 (1.11)+	6.17 (1.44)

Appendix B(7): Lleonart *et al.* procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error y_1 = K	-1.92 (1.26)	-5.49 (0.91)	0.71 (5.71)+	-6.23 (1.20)	-5.28 (1.70)
Observation Error y_1 estimated	27.70 (6.13)	38.90 (11.88)	28.06 (5.85)	22.04 (5.87)	20.44 (5.50)
Process Error Unsmoothed cpue data q estimated	65.81 (4.03)	32.85 (2.32)	44.41 (2.93)	58.52 (3.85)	43.46 (2.94)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	23.12 (1.59)	13.72 (1.10)	14.41 (1.45)	17.71 (1.52)	13.27 (1.44)
Process Error Unsmoothed cpue data Linear method	15.48 (1.33)	10.88 (0.99)	8.60 (1.26)	10.41 (1.27)	7.50 (1.25)
Process Error Smoothed cpue data q estimated	40.83 (3.84)	15.84 (1.98)	32.72 (3.35)	34.65 (3.68)	28.96 (3.25)
Process Error Smoothed cpue data $(C/E)_1$ = qK	12.49 (1.30)	2.80 (1.02)	9.47 (1.40)	7.55 (1.25)	6.26 (9.55)+
Process Error Smoothed cpue data Linear method	5.62 (1.20)	0.25 (0.94)+	3.53 (1.29)	0.98 (1.15)+	0.48 (1.25)+

Appendix B(8): Lleonart *et al.* procedure (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error Y_1 = K	-17.68 (0.65)	-6.91 (0.72)	-13.27 (1.06)	-9.37 (0.72)	-6.06 (1.15)
Observation Error Y_1 estimated	*	*	*	*	*
Process Error Unsmoothed cpue data q estimated	32.52 (2.13)	29.52 (1.67)	-9.19 (1.17)	45.92 (2.35)	-1.63 (1.35)+
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	-7.50 (0.76)	16.57 (0.72)	-25.80 (0.69)	1.74 (0.83)	-19.63 (0.75)
Process Error Unsmoothed cpue data Linear method	-11.30 (0.65)	16.20 (0.69)	-27.42 (0.66)	-2.34 (0.71)	-21.38 (0.72)
Process Error Smoothed cpue data q estimated	19.94 (1.96)	16.61 (1.48)	-1.66 (1.42)+	32.06 (2.15)	6.52 (1.58)
Process Error Smoothed cpue data $(C/E)_1$ = qK	-15.67 (0.67)	5.00 (0.75)	-24.38 (0.70)	-7.15 (0.73)	-18.10 (0.77)
Process Error Smoothed cpue data Linear method	-19.19 (0.64)	4.59 (0.72)	-26.69 (0.66)	-11.02 (0.70)	-20.60 (0.72)

Appendix B(9): Schnute-77 procedure (based on the Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error (1) Y_1 = K	-9.53 (0.72)	8.72 (0.77)	-0.53 (1.13)+	-0.34 (0.80)+	7.74 (1.22)
Observation Error (1) Y_1 estimated	4.02 (1.70)	14.14 (1.16)	11.98 (1.88)	14.53 (1.87)	21.28 (2.04)
Observation Error (2) Y_1 = K	-11.37 (0.71)	6.68 (0.76)	-2.72 (1.11)	-2.42 (0.78)	5.37 (1.20)
Observation Error (2) Y_1 estimated	1.67 (1.42)+	11.91 (1.03)	9.22 (1.65)	11.95 (1.56)	18.30 (1.79)
Process Error Unsmoothed cpue data q estimated	19.92 (1.70)	28.15 (1.36)	28.84 (2.02)	32.03 (1.89)	39.55 (2.19)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	-6.02 (0.82)	18.39 (0.67)	2.36 (1.13)	3.48 (0.90)	10.86 (1.23)
Process Error Unsmoothed cpue data Linear method	-10.27 (0.67)	17.42 (0.62)	-2.03 (1.01)	-1.20 (0.74)+	6.11 (1.09)
Process Error Smoothed cpue data q estimated	0.81 (1.31)+	12.38 (1.03)	6.86 (1.52)	11.00 (1.44)	15.74 (1.64)
Process Error Smoothed cpue data $(C/E)_1$ = qK	-13.73 (0.67)	7.35 (0.70)	-7.98 (0.98)	-5.02 (0.74)	-0.33 (1.06)+
Process Error Smoothed cpue data Linear method	-17.61 (0.64)	6.54 (0.66)	-12.03 (0.93)	-9.29 (0.71)	-4.72 (1.00)

Appendix B(10): Shepherd procedure

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	42.60 (8.36)	17.38 (1.62)	54.70 (9.85)	26.61 (2.17)	34.23 (2.73)
Observation Error y_1 estimated	141.60 (30.95)	40.55 (4.83)	154.02 (30.61)	76.94 (10.35)	83.65 (10.14)
Process Error Unsmoothed cpue data q estimated	302.91 (27.56)	66.70 (3.53)	342.28 (21.53)	94.25 (5.21)	108.74 (6.04)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	*	470.13 (59.58)	*	911.83 (121.62)	928.58 (121.06)
Process Error Unsmoothed cpue data Linear method	??	??	??	??	??
Process Error Smoothed cpue data q estimated	253.51 (28.95)	74.37 (5.37)	274.00 (31.76)	150.10 (9.92)	157.65 (10.36)
Process Error Smoothed cpue data $(C/E)_1 = qK$	41.15 (3.97)	23.24 (1.59)	50.73 (4.78)	32.12 (2.30)	38.22 (2.87)
Process Error Smoothed cpue data Linear method	??	??	??	??	??

Appendix B(11): Schnute-85 procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	-17.51 (0.54)	-19.32 (0.01)	-28.46 (0.73)	-19.94 (0.54)	-31.70 (0.70)
Observation Error y_1 estimated	-97.53 (0.02)!	-37.19 (0.00)!	-98.62 (0.01)!	-97.61 (0.00)!	-98.67 (0.01)!

Note: ! See discussion in Chapter 10

Appendix B(12): TLS based procedures

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Butterworth-Andrew (Schaefer form) $y_1 = K$	-14.57 (0.60)	7.45 (0.60)	-9.62 (0.92)	-5.94 (0.66)	-2.11 (0.99)
Butterworth-Andrew (Schaefer form) y_1 estimated	-4.59 (1.23)	11.50 (0.92)	0.56 (1.40)+	5.05 (1.35)	8.92 (1.52)
Butterworth-Andrew (Fox form) $y_1 = K$	21.89 (1.15)	13.64 (0.93)	28.44 (1.58)	16.53 (1.10)	20.80 (1.48)
Butterworth-Andrew (Fox form) y_1 estimated	43.38 (3.51)	23.11 (1.84)	50.14 (3.58)	37.09 (3.36)	41.21 (3.37)
Ricker Model $y_1 = K$	-3.08 (1.29)	11.83 (1.25)	7.60 (1.45)	8.13 (1.44)	18.09 (1.60)
Power Model $y_1 = K$	85.07 (11.84)	43.80 (6.41)	102.31 (12.32)	76.84 (11.31)	90.18 (11.58)

Appendix C: Butterworth age-structured operating model with process error only: as for Appendix A except that all artificial data sets used in the estimation of the biases are generated using σ_q = 0.0 and σ_r = 0.3. Tables (1) to (12) below contain the results of the following simulations :

Table	Details of estimation procedures used
1	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)
2	Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)
3	Babayan-Kizner procedure (Fox and Schaefer forms)
4	Butterworth-Andrew procedure (Fox form)
5	Butterworth-Andrew procedure (Schaefer form)
6	Horbowy-Draganik procedure (Pella-Tomlinson model)
7	Lleonart *et al.* procedure (Fox form)
8	Lleonart *et al.* procedure (Schaefer form)
9	Schnute-77 procedure (based on the Schaefer model)
10	Shepherd procedure
11	Schnute-85 procedure (Fox form)
12	TLS based procedures

Appendix C(1): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Linear Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	81.71 (3.85)	53.39 (2.99)	70.89 (3.62)
Brown Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	62.16 (3.49)	53.39 (2.99)	52.51 (3.28)
Maximum Entropy Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	64.03 (3.39)	53.39 (2.99)	54.27 (3.19)
ARIMA Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	62.35 (14.95)	53.39 (2.99)	52.69 (14.06)
Exponential Smoothing Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	63.81 (3.38)	53.39 (2.99)	54.06 (3.18)
Adaptive (Lag 0) Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	60.19 (4.03)	53.39 (2.99)	50.63 (3.79)
Adaptive (Lag 1) Unsmoothed cpue data	60.44 (3.13)	43.12 (2.20)	64.22 (3.31)	53.39 (2.99)	54.50 (3.11)
Linear Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	84.57 (4.09)	56.28 (3.17)	73.58 (3.85)
Brown Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	72.16 (3.71)	56.28 (3.17)	61.91 (3.49)
Maximum Entropy Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	69.20 (3.74)	56.28 (3.17)	59.13 (3.52)
ARIMA Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	56.33 (8.99)	56.28 (3.17)	47.03 (8.45)
Exponential Smoothing Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	70.84 (3.63)	56.28 (3.17)	60.67 (3.42)
Adaptive (Lag 0) Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	70.12 (3.59)	56.28 (3.17)	59.99 (3.37)
Adaptive (Lag 1) Smoothed cpue data	63.46 (3.32)	44.83 (2.35)	69.36 (3.59)	56.28 (3.17)	59.28 (3.37)

Appendix C(2): Babayan *et al.* time series procedure; $E_{0.1}$ estimation by Gulland functional regression (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Linear Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	32.15 (1.81)	28.78 (1.40)	43.13 (1.96)
Brown Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	17.94 (1.64)	28.78 (1.40)	27.74 (1.71)
Maximum Entropy Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	19.28 (1.47)	28.78 (1.40)	29.19 (1.59)
ARIMA Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	18.70 (10.62)+	28.78 (1.40)	28.56 (11.51)
Exponential Smoothing Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	19.31 (1.50)	28.78 (1.40)	29.22 (1.59)
Adaptive (Lag 0) Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	16.64 (2.26)	28.78 (1.40)	26.33 (2.44)
Adaptive (Lag 1) Unsmoothed cpue data	16.96 (1.27)	33.86 (1.27)	19.59 (1.41)	28.78 (1.40)	29.53 (4.72)
Linear Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	32.87 (1.92)	29.92 (1.49)	43.91 (2.10)
Brown Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	24.02 (1.61)	29.92 (1.49)	34.33 (1.74)
Maximum Entropy Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	21.74 (1.65)	29.92 (1.49)	31.86 (1.78)
ARIMA Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	12.39 (6.15)	29.92 (1.49)	21.73 (6.66)
Exponential Smoothing Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	23.06 (1.58)	29.92 (1.49)	33.29 (1.71)
Adaptive (Lag 0) Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	22.61 (1.56)	29.92 (1.49)	32.80 (1.69)
Adaptive (Lag 1) Smoothed cpue data	17.99 (1.36)	34.54 (1.37)	22.00 (1.55)	29.92 (1.49)	32.14 (1.68)

Appendix C(3): Babayan-Kizner procedure (Fox and Schaefer forms)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Unsmoothed cpue data q estimated (Fox)	89.32 (13.97)	47.58 (7.75)	176.77 (13.38)	81.01 (13.36)	160.30 (12.58)
Unsmoothed cpue data $(C/E)_1$ = qK (Fox)	29.37 (1.91)	19.15 (1.76)	112.35 (3.03)	23.68 (1.83)	92.51 (3.38)
Unsmoothed cpue data Linear method (Fox)	20.94 (1.69)	15.73 (1.61)	92.90 (3.31)	15.63 (1.62)	81.42 (3.12)
Smoothed cpue data q estimated (Fox)	97.84 (7.53)	50.63 (5.21)	180.09 (13.74)	89.15 (7.35)	163.42 (12.92)
Smoothed cpue data $(C/E)_1$ = qK (Fox)	31.74 (2.08)	19.52 (1.89)	103.02 (3.70)	25.96 (1.99)	90.93 (3.48)
Smoothed cpue data Linear method (Fox)	22.32 (1.83)	15.56 (1.72)	90.26 (3.38)	16.95 (1.75)	78.94 (3.18)
Unsmoothed cpue data q estimated (Sch.)	14.98 (6.51)	23.96 (4.87)	12.42 (6.23)	26.50 (7.16)	21.76 (6.75)
Unsmoothed cpue data $(C/E)_1$ = qK (Sch.)	-12.39 (1.02)	9.68 (1.27)	-15.11 (1.23)	-3.54 (1.11)	-8.05 (1.33)
Unsmoothed cpue data Linear method (Sch.)	-17.15 (0.93)	7.79 (1.21)	-19.79 (1.12)	-8.77 (1.02)	-13.12 (1.21)
Smoothed cpue data q estimated (Sch.)	16.57 (6.10)	23.78 (4.51)	15.02 (5.91)	28.35 (6.70)	24.57 (6.40)
Smoothed cpue data $(C/E)_1$ = qK (Sch.)	-11.60 (1.16)	8.96 (1.37)	-13.58 (1.35)	-2.67 (1.23)	-6.34 (1.46)
Smoothed cpue data Linear method (Sch.)	-16.88 (1.01)	6.76 (1.29)	18.84 (1.22)	-8.48 (1.11)	-12.10 (1.32)

Appendix C(4): Butterworth-Andrew procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	32.84 (2.24)	21.32 (1.95)	42.96 (3.01)	27.00 (2.08)	34.45 (2.83)
Observation Error y_1 estimated	311.79 (100.77)	162.19 (81.72)	316.56 (150.72)	293.62 (112.38)	291.75 (141.73)
Process Error Unsmoothed cpue data q estimated	98.48 (6.59)	51.83 (3.89)	82.33 (12.71)	106.81 (2.48)	89.76 (11.54)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	34.80 (1.91)	24.16 (1.76)	41.68 (2.30)	28.88 (1.83)	33.24 (2.16)
Process Error Unsmoothed cpue data Linear method	25.56 (1.72)	20.13 (1.62)	32.11 (2.73)	20.04 (1.64)	24.25 (1.95)
Process Error Smoothed cpue data q estimated	104.57 (8.94)	53.68 (4.75)	113.64 (9.44)	95.58 (8.55)	100.93 (8.88)
Process Error Smoothed cpue data $(C/E)_1 = qK$	36.50 (2.10)	23.83 (1.91)	43.64 (2.55)	30.50 (2.01)	35.10 (2.40)
Process Error Smoothed cpue data Linear method	26.29 (1.86)	19.30 (1.73)	33.06 (2.27)	20.74 (1.77)	25.14 (2.13)

Appendix C(5): Butterworth-Andrew procedure (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	-7.94 (1.20)	12.43 (1.41)	0.73 (1.70)+	1.30 (1.32)+	9.10 (1.84)
Observation Error y_1 estimated	152.70 (91.28)+	111.62 (60.78)+	170.39 (110.02)+	178.23 (108.34)+	192.85 (119.16)+
Process Error Unsmoothed cpue data q estimated	18.20 (2.20)	25.59 (2.10)	23.66 (2.42)	30.14 (2.42)	33.93 (2.62)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	-9.45 (1.04)	13.36 (1.30)	-4.47 (1.29)	-0.29 (1.15)+	3.47 (1.40)
Process Error Unsmoothed cpue data Linear method	-14.99 (0.99)	10.58 (1.29)	-10.27 (1.23)	-6.40 (1.10)	-2.82 (1.33)
Process Error Smoothed cpue data q estimated	-9.02 (1.15)	12.18 (1.41)	-3.96 (1.42)	17.50 (1.48)	4.02 (1.42)
Process Error Smoothed cpue data $(C/E)_1 = qK$	18.89 (2.58)	24.97 (2.36)	24.61 (2.85)	30.90 (2.84)	34.96 (3.09)
Process Error Smoothed cpue data Linear method	-15.06 (1.04)	9.08 (1.36)	-10.28 (1.32)	-6.48 (1.17)	-2.83 (1.43)

Appendix C(6): Horbowy-Draganik procedure (Pella-Tomlinson model)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	*	*	*	*	*
Observation Error y_1 estimated	*	*	*	*	*
Process Error Unsmoothed cpue data q estimated	92.03 (5.53)	48.37 (3.53)	99.90 (5.79)	64.27 (4.76)	68.22 (4.91)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	31.80 (1.86)	21.97 (1.72)	38.41 (2.23)	12.46 (1.59)	16.17 (1.88)
Process Error Unsmoothed cpue data Linear method	31.40 (1.55)	26.49 (1.16)	42.44 (2.13)	11.83 (1.32)	14.25 (1.78)
Process Error Smoothed cpue data q estimated	92.58 (5.32)	47.70 (3.54)	100.90 (5.69)	64.45 (4.57)	68.78 (4.82)
Process Error Smoothed cpue data $(C/E)_1 = qK$	26.71 (1.36)	16.13 (1.05)	34.58 (1.81)	7.84 (1.15)	12.67 (1.52)
Process Error Smoothed cpue data Linear method	24.15 (1.78)	17.67 (1.67)	30.69 (2.18)	5.74 (1.51)	9.45 (1.83)

Appendix C(7): Lleonart *et al.* procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error $y_1 = K$	-71.99 (2.77)	*	-71.28 (3.04)	-73.23 (2.64)	-72.99 (2.86)
Observation Error y_1 estimated	51.54 (21.34)	*	45.57 (19.68)	44.89 (2.04)	36.90 (18.51)
Process Error Unsmoothed cpue data q estimated	39.93 (4.77)	19.70 (2.79)	30.37 (4.19)	33.79 (4.56)	26.76 (4.05)
Process Error Unsmoothed cpue data $(C/E)_1 = qK$	-13.36 (0.92)	8.45 (1.15)	24.42 (0.68)	-4.61 (1.01)	-18.14 (0.74)
Process Error Unsmoothed cpue data Linear method	9.96 (1.61)	5.19 (1.51)	5.53 (1.46)	5.13 (1.53)	2.51 (1.43)+
Process Error Smoothed cpue data q estimated	41.70 (5.07)	19.65 (2.92)	33.31 (4.53)	35.47 (4.84)	29.24 (4.37)
Process Error Smoothed cpue data $(C/E)_1 = qK$	19.76 (1.98)	8.64 (1.79)	14.73 (1.85)	14.50 (1.89)	11.20 (1.81)
Process Error Smoothed cpue data Linear method	11.07 (1.72)	4.91 (1.62)	7.37 (1.65)	6.19 (1.65)	4.03 (1.61)

Appendix C(8): Lleonart *et al.* procedure (Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error Y_1 = K	*	3.95 (1.26)	17.49 (1.84)	*	-10.63 (2.00)
Observation Error Y_1 estimated	*	*	*	*	*
Process Error Unsmoothed cpue data q estimated	19.64 (2.54)	20.65 (2.14)	-2.95 (1.94)+	31.73 (2.79)	5.12 (2.10)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	17.79 (1.81)	8.49 (1.67)	12.03 (1.62)	12.62 (1.73)	8.86 (1.59)
Process Error Unsmoothed cpue data Linear method	-17.38 (0.84)	7.50 (1.10)	-26.87 (0.65)	-9.03 (0.92)	-20.78 (0.70)
Process Error Smoothed cpue data q estimated	20.98 (2.63)	20.50 (2.21)	-0.27 (2.10)+	33.21 (2.89)	8.61 (2.28)
Process Error Smoothed cpue data $(C/E)_1$ = qK	-12.86 (1.00)	7.44 (1.24)	-22.91 (0.81)	-4.06 (1.10)	-16.50 (0.87)
Process Error Smoothed cpue data Linear method	-17.35 (0.90)	6.17 (1.17)	-25.81 (0.76)	-1.10 (1.08)+	-19.64 (0.82)

Appendix C(9): Schnute-77 procedure (based on the Schaefer form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error (1) Y_1 = K	-5.82 (1.21)	13.36 (1.41)	2.91 (1.72)+	3.70 (1.34)	11.46 (1.86)
Observation Error (1) Y_1 estimated	16.84 (4.92)	26.51 (3.38)	25.65 (5.35)	28.70 (5.42)	36.09 (5.79)
Observation Error (2) Y_1 = K	-7.61 (1.07)	11.60 (1.25)	0.74 (1.55)+	1.73 (1.18)+	9.11 (1.68)
Observation Error (2) Y_1 estimated	8.17 (2.25)	19.58 (1.65)	16.26 (2.63)	19.11 (2.48)	25.92 (2.84)
Process Error Unsmoothed cpue data q estimated	3.22 (1.73)+	17.60 (1.61)	9.19 (2.02)	13.65 (1.91)	18.26 (2.18)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	-10.93 (0.90)	11.50 (1.13)	-5.51 (1.24)	-1.93 (0.99)+	2.34 (1.34)+
Process Error Unsmoothed cpue data Linear method	-15.43 (0.81)	10.02 (1.06)	-10.13 (1.14)	-6.88 (0.89)	-2.66 (1.23)
Process Error Smoothed cpue data q estimated	2.81 (1.76)+	16.33 (1.66)	8.78 (2.07)	13.20 (1.94)	17.81 (2.24)
Process Error Smoothed cpue data $(C/E)_1$ = qK	-10.30 (0.98)	10.60 (1.21)	-4.93 (1.31)	-1.23 (1.08)+	2.97 (1.42)
Process Error Smoothed cpue data Linear method	-15.22 (0.87)	8.89 (1.12)	-9.99 (1.19)	-6.66 (0.96)	-2.51 (1.29)+

Appendix C(10): Shepherd procedure

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error Y_1 = K	165.29 (73.70)	37.49 (5.76)	193.39 (96.21)	53.22 (8.61)	62.56 (10.92)
Observation Error Y_1 estimated	*	333.89 (443.91)+	*	*	714.83 (230.06)
Process Error Unsmoothed cpue data q estimated	396.19 (55.37)	88.15 (7.54)	423.65 (58.92)	155.56 (11.63)	162.91 (12.26)
Process Error Unsmoothed cpue data $(C/E)_1$ = qK	122.65 (19.48)	38.86 (3.68)	138.56 (21.70)	52.99 (4.90)	59.07 (5.49)
Process Error Unsmoothed cpue data Linear method	??	??	??	??	??
Process Error Smoothed cpue data q estimated	272.10 (37.84)	79.88 (7.61)	298.50 (41.48)	142.84 (11.85)	152.37 (12.81)
Process Error Smoothed cpue data $(C/E)_1$ = qK	87.44 (14.40)	34.36 (3.41)	102.09 (16.70)	48.05 (4.54)	54.67 (5.34)
Process Error Smoothed cpue data Linear method	??	??	??	??	??

Appendix C(11): Schnute-85 procedure (Fox form)

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Observation Error Y_1 = K	14.11 (1.49)	-19.32 (0.01)	-28.46 (0.73)	-19.94 (0.54)	-31.70 (0.70)
Observation Error Y_1 estimated	-97.59 (0.00)!	-37.19 (0.00)!	-98.65 (0.02)!	-97.68 (0.00)!	-98.71 (0.00)!

Note: ! See discussion in Chapter 10

Appendix C(12): TLS based procedures

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Butterworth-Andrew (Schaefer form) Y_1 = K	-11.57 (0.93)	10.87 (1.17)	-6.97 (1.20)	-2.63 (1.02)	0.77 (1.30)+
Butterworth-Andrew (Schaefer form) Y_1 estimated	3.11 (4.56)+	19.01 (3.38)	7.93 (4.38)+	13.53 (5.02)	16.90 (4.75)
Butterworth-Andrew (Fox form) Y_1 = K	28.30 (1.78)	19.32 (1.66)	34.66 (2.22)	22.67 (1.71)	26.64 (2.09)
Butterworth-Andrew (Fox form) Y_1 estimated	49.70 (4.60)	29.76 (9.44)	57.18 (5.03)	43.13 (4.40)	47.83 (4.73)
Ricker Model Y_1 = K	95.70 (14.04)	60.90 (11.22)	112.58 (14.35)	87.00 (13.42)	99.82 (13.49)
Power Model Y_1 = K	0.18 (2.60)+	18.16 (2.42)	10.57 (2.83)	11.80 (2.93)	21.41 (3.13)

Appendix D: Estimates of the percentage bias in the estimates of the parameters and variables used in the management of the ICSEAF hake stocks for the estimation procedures listed in Table 9.5. The standard error of the percentage bias estimate is given in parenthesis. Column 1 in each Table contains the acronym for the procedure. Tables (1) to (17) below contain the results of the following simulations carried out to test the procedures for robustness:

Table	Alterations made to the age-structured operating model	
1	$\sigma_r = 0.13;\ \sigma_q = 0.0$	+
2	$\sigma_r = 0.1;\ \sigma_q = 0.2$	
3	$\sigma_r = 0.0;\ \sigma_q = 0.3$	+
4	$\sigma_r = 0.2;\ \sigma_q = 0.2$	+
5	$M = 0.2$	*
6	$M = 0.4$	*
7	$M = 0.5$	*
8	$a_m = 3$	
9	$a_m = 5$	
10	$a_r = 4$	
11	$\delta = 1.0$	
12	$\delta = 0.25$	
13	MSY = 200	
14	MSY = 300	
15	$B^e_{MSY}/K^e = 0.3$	
16	$B^e_{MSY}/K^e = 0.45$	
17	$N_{1,a} = N_{0,0}\, e^{-aM_e^{\varepsilon_y}}$ $\varepsilon_y \sim N(0;\sigma_r^2)$	

Note: * procedures that use a value of M (for these tests only Schnute-85) continue to assume that M = 0.3
+ otherwise the standard specification is the mixed error structure: $\sigma_r = 0.2$, $\sigma_q = 0.1$

Appendix D(1): $\sigma_r = 0.13$; $\sigma_q = 0.0$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	38.54 (0.97)	26.63 (0.38)	24.50 (2.28)	32.45 (0.93)	17.09 (2.14)
Bn-S-GNU	6.14 (0.54)	23.12 (0.23)	-4.71 (1.68)	16.87 (0.60)	3.21 (1.82)
BK-F-PLS	11.44 (1.07)	5.94 (0.55)	81.93 (2.23)	6.55 (1.02)	71.10 (2.10)
BK-S-PFU	-15.73 (0.88)	5.97 (0.56)	-17.74 (1.12)	-7.21 (0.97)	-10.90 (1.21)
BA-F-OK	19.15 (0.69)	8.31 (0.43)	29.16 (1.06)	13.92 (0.66)	21.48 (1.00)
BA-S-OK	-15.06 (0.42)	3.49 (0.38)	-6.14 (0.77)	-6.47 (0.46)	1.66 (0.83)
BA-F-PLS	17.03 (1.18)	11.16 (0.62)	25.58 (1.71)	11.89 (1.13)	18.11 (1.61)
BA-S-PLS	-19.28 (0.73)	4.42 (0.57)	-13.11 (1.16)	-11.13 (0.81)	-5.88 (1.25)
HD-PT-PLS	14.74 (1.16)	9.39 (0.60)	23.01 (1.67)	-2.22 (0.99)	3.12 (1.40)
LI-F-PLS	-21.14 (0.57)	2.30 (0.47)	-27.80 (0.71)	-13.17 (0.63)	-21.80 (0.77)
LI-S-PFU	-7.27 (0.80)	17.02 (0.49)	-27.83 (0.77)	2.10 (0.88)	-21.82 (0.83)
S71-S-OK	-12.41 (0.45)	5.16 (0.41)	-3.14 (0.79)	-3.56 (0.49)	4.91 (0.86)
S72-S-OK	-14.43 (0.43)	2.96 (0.39)	-5.57 (0.78)	-5.78 (0.47)	2.28 (0.84)
S7-S-PFS	-16.22 (0.63)	4.46 (0.44)	-10.13 (0.94)	-7.75 (0.69)	-2.66 (1.02)
S8-F-OK	-12.37 (0.16)	-17.70 (0.00)	-22.10 (0.00)	-14.96 (0.16)	-25.63 (0.00)
BA-S-TK	-17.05 (0.50)	4.52 (0.41)	-11.80 (0.89)	-8.67 (0.56)	-4.47 (0.97)

Appendix D(2): $\sigma_r = 0.1$; $\sigma_q = 0.2$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	46.49 (1.52)	32.89 (0.93)	34.27 (2.53)	40.05 (1.46)	26.28 (2.38)
Bn-S-GBU	10.01 (0.73)	27.15 (0.53)	0.48 (1.60)+	21.12 (0.80)	8.83 (1.73)
BK-F-PLS	16.17 (1.24)	10.36 (0.98)	86.42 (2.49)	11.07 (1.19)	75.32 (2.34)
BK-S-PFU	-13.98 (0.81)	8.39 (0.77)	-16.41 (1.03)	-5.29 (0.89)	-9.47 (1.12)
BA-F-OK	25.01 (1.29)	13.86 (1.05)	34.96 (1.82)	19.52 (1.23)	26.93 (1.71)
BA-S-OK	-11.98 (0.70)	7.32 (0.75)	-3.19 (1.09)	-3.09 (0.77)	4.85 (1.19)
BA-F-PLS	21.39 (1.32)	15.25 (1.03)	29.21 (1.75)	16.06 (1.27)	21.52 (1.65)
BA-S-PLS	-17.15 (0.76)	7.05 (0.81)	-11.56 (1.08)	-8.78 (0.84)	-4.21 (1.17)
HD-PT-PLS	18.84 (1.28)	13.42 (1.00)	26.41 (1.71)	1.46 (1.11)+	6.17 (1.44)
L1-F-PLS	5.62 (1.20)	0.25 (0.94)+	3.53 (1.29)	0.98 (1.15)+	0.48 (1.25)+
L1-S-PFU	-7.50 (0.76)	16.57 (0.72)	-25.80 (0.69)	1.74 (0.83)	-19.63 (0.75)
S71-S-OK	-9.53 (0.72)	8.72 (0.77)	-0.53 (1.13)+	-0.34 (0.80)+	7.74 (1.22)
S72-S-OK	-11.37 (0.71)	6.82 (0.76)	-2.72 (1.11)	-2.42 (0.78)	5.37 (1.20)
S7-S-PFS	-13.73 (0.67)	7.35 (0.70)	-7.98 (0.98)	-5.02 (0.74)	-0.33 (1.06)+
S8-F-OK	-17.51 (0.54)	-19.32 (0.01)	-28.46 (0.73)	-19.94 (0.54)	-31.70 (0.70)
BA-S-TK	-14.57 (0.60)	7.45 (0.66)	-9.62 (0.92)	-5.94 (0.66)	-2.11 (1.00)

Appendix D(3): $\sigma_r = 0.0$; $\sigma_q = 0.3$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	60.44 (3.13)	43.12 (2.20)	62.16 (3.49)	53.39 (2.99)	52.51 (3.28)
Bn-S-GBU	16.96 (1.27)	33.86 (1.27)	17.94 (1.64)	28.78 (1.40)	27.74 (1.71)
BK-F-PLS	22.32 (1.83)	15.56 (1.72)	90.26 (3.38)	16.95 (1.75)	78.94 (3.18)
BK-S-PFU	-12.39 (1.02)	9.68 (1.27)	-15.11 (1.23)	-3.54 (1.11)	-8.05 (1.33)
BA-F-OK	32.84 (2.24)	21.32 (1.95)	42.96 (3.01)	27.00 (2.08)	34.45 (2.83)
BA-S-OK	-7.94 (1.20)	12.43 (1.41)	0.73 (1.70)+	1.30 (1.32)+	9.10 (1.84)
BA-F-PLS	26.29 (1.86)	19.30 (1.73)	33.06 (2.27)	20.74 (1.77)	25.14 (2.13)
BA-S-PLS	-15.06 (1.04)	9.08 (1.36)	-10.28 (1.32)	-6.48 (1.17)	-2.83 (1.43)
HD-PT-PLS	24.15 (1.78)	17.67 (1.67)	30.69 (2.18)	5.74 (1.51)	9.45 (1.83)
L1-F-PLS	11.07 (1.72)	4.91 (1.62)	7.37 (1.65)	6.19 (1.65)	4.03 (1.61)
L1-S-PFU	17.79 (1.81)	8.49 (1.67)	12.03 (1.62)	12.62 (1.73)	8.86 (1.59)
S71-S-OK	-5.82 (1.21)	13.36 (1.41)	2.91 (1.72)+	3.70 (1.34)	11.46 (1.86)
S72-S-OK	-7.61 (1.07)	11.60 (1.25)	0.74 (1.55)+	1.73 (1.18)+	9.11 (1.68)
S7-S-PFS	-10.30 (0.98)	10.60 (1.21)	-4.93 (1.31)	-1.23 (1.08)+	2.97 (1.42)
S8-F-OK	14.11 (1.49)	-19.32 (0.01)	-28.46 (0.73)	-19.94 (0.54)	-31.70 (0.70)
BA-S-TK	-11.57 (0.93)	10.87 (1.17)	-6.97 (1.20)	-2.63 (1.02)	0.77 (1.30)

Appendix D(4): σ_r = 0.2; σ_q = 0.2

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	20.77 (2.10)	23.10 (1.27)	10.21 (3.78)	15.47 (2.07)	3.66 (3.55)+
Bn-S-GBU	-0.07 (1.02)+	24.78 (0.84)	-8.88 (2.72)	10.02 (1.12)	-1.31 (2.94)+
BK-F-PLS	22.28 (2.53)	15.40 (1.62)	98.69 (4.38)	16.91 (2.42)	86.87 (4.12)
BK-S-PFU	6.40 (9.69)+	31.01 (11.83)	10.51 (13.36)+	17.15 (10.67)+	19.70 (14.47)+
BA-F-OK	24.73 (1.82)	13.39 (1.37)	35.08 (2.51)	19.25 (1.74)	27.05 (2.36)
BA-S-OK	-12.06 (1.02)	7.13 (1.05)	-2.80 (1.58)+	-3.17 (1.12)	5.28 (1.72)
BA-F-PLS	30.13 (2.84)	22.45 (1.82)	42.66 (3.80)	24.42 (2.71)	34.17 (3.57)
BA-S-PLS	-13.01 (1.72)	11.79 (1.64)	-4.26 (2.38)+	-4.22 (1.90)	3.70 (2.57)+
HD-PT-PLS	27.29 (2.67)	20.32 (1.66)	39.16 (3.63)	8.33 (2.27)	16.50 (3.04)
Ll-F-PLS	14.19 (2.38)	7.55 (1.44)	12.11 (2.14)	9.17 (2.27)	9.53 (2.49)
Ll-S-PFU	6.35 (1.69)	33.70 (1.14)	-35.24 (1.22)	17.10 (1.86)	-29.84 (1.32)
S71-S-OK	-7.41 (1.06)	11.02 (1.11)	2.69 (1.69)+	1.95 (1.21)+	11.23 (1.83)
S72-S-OK	-11.10 (1.00)	6.86 (1.01)	-2.02 (1.56)+	-2.12 (1.10)+	6.12 (1.69)
S7-S-PFS	-8.99 (1.37)	13.75 (1.07)	-0.94 (1.91)+	0.20 (1.50)+	7.29 (2.07)
S8-F-OK	-1.23 (0.70)+	-11.75 (0.05)	-9.24 (0.93)	-4.15 (0.69)	-13.36 (0.89)
BA-S-TK	-11.42 (1.02)	11.76 (0.93)	-4.63 (1.64)	-2.47 (1.12)	3.30 (1.78)

Appendix D(5): M = 0.2

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	43.09 (1.32)	27.87 (0.74)	27.16 (2.11)	26.95 (1.17)	10.64 (1.98)
Bn-S-GBU	12.27 (0.63)	26.33 (0.40)	-0.50 (1.40)+	23.75 (0.69)	7.82 (1.52)
BK-F-PLS	13.12 (1.00)	7.96 (0.78)	90.24 (2.17)	8.27 (0.95)	79.00 (2.04)
BK-S-PFU	-12.84 (0.66)	10.03 (0.63)	-16.47 (0.88)	-3.93 (0.73)	-9.50 (0.96)
BA-F-OK	20.90 (1.00)	10.56 (0.81)	30.36 (1.49)	15.71 (0.96)	22.65 (1.40)
BA-S-OK	-10.05 (0.55)	9.16 (0.57)	-0.37 (0.96)+	-0.86 (0.60)+	7.95 (1.04)
BA-F-PLS	18.28 (1.05)	12.83 (0.80)	26.24 (1.48)	13.20 (1.01)	18.77 (1.39)
BA-S-PLS	-15.19 (0.64)	10.09 (0.67)	-9.06 (0.97)	-6.53 (0.70)	-1.46 (1.05)+
HD-PT-PLS	15.84 (1.04)	10.71 (0.79)	23.50 (1.45)	-1.42 (0.89)+	3.32 (1.22)
Ll-F-PLS	0.74 (1.00)+	-3.94 (0.77)	-4.34 (1.02)	-3.58 (0.95)	-3.07 (1.05)
Ll-S-PFU	-7.27 (0.63)	17.24 (0.67)	-23.07 (0.69)	2.21 (0.70)	-16.63 (0.75)
S71-S-OK	-7.09 (0.60)	10.58 (0.60)	2.96 (1.03)	2.41 (0.67)	11.56 (1.11)
S72-S-OK	-9.27 (0.56)	8.28 (0.57)	0.22 (0.98)+	0.01 (0.62)+	8.59 (1.06)
S7-S-PFS	-12.30 (0.55)	9.18 (0.57)	-6.12 (0.86)	-3.33 (0.61)	1.72 (0.93)+
S8-F-OK	9.00 (0.86)	-10.66 (0.08)	-0.42 (1.28)+	5.89 (0.83)	-4.91 (1.22)
BA-S-TK	-12.62 (0.49)	9.70 (0.53)	-7.41 (0.81)	-3.69 (0.54)	0.32 (0.88)+

Appendix D(6): M = 0.4

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	47.29 (2.03)	36.56 (1.32)	39.82 (2.93)	40.70 (1.94)	31.48 (2.76)
Bn-S-GBU	7.67 (0.45)	27.90 (0.87)	1.98 (1.78)+	18.44 (1.09)	10.44 (1.92)
BK-F-PLS	19.30 (1.56)	12.81 (1.27)	83.30 (2.92)	13.96 (1.49)	72.37 (2.75)
BK-S-PFU	-13.89 (1.02)	8.28 (1.01)	-15.57 (1.24)	-5.27 (1.13)	-8.57 (1.35)
BA-F-OK	28.68 (1.66)	16.94 (1.40)	38.69 (2.23)	22.93 (1.59)	30.42 (2.10)
BA-S-OK	-13.26 (0.90)	6.10 (1.01)	-5.36 (1.30)	-4.58 (0.99)	2.49 (1.40)+
BA-F-PLS	24.84 (1.66)	17.95 (1.32)	32.44 (2.11)	19.26 (1.59)	24.54 (1.98)
BA-S-PLS	-18.18 (0.97)	5.21 (1.05)	-13.07 (1.27)	-9.99 (1.06)	-5.86 (1.37)
HD-PT-PLS	22.72 (1.63)	16.36 (1.30)	30.13 (2.07)	4.46 (1.39)	9.03 (1.74)
L1-F-PLS	10.61 (1.49)	4.49 (1.19)	7.72 (1.55)	5.66 (1.43)	4.30 (1.50)
L1-S-PFU	-6.13 (0.96)	18.18 (0.89)	-27.28 (0.73)	3.27 (1.05)	-21.24 (0.79)
S71-S-OK	-11.04 (0.92)	7.60 (1.02)	-2.94 (1.32)	-2.14 (1.01)	5.11 (1.43)
S72-S-OK	-12.91 (0.89)	5.75 (0.99)	-5.16 (1.28)	-4.19 (0.98)	2.70 (1.39)
S7-S-PFS	-14.07 (0.84)	6.90 (0.90)	-8.76 (1.15)	-5.47 (0.93)	-1.19 (1.25)+
S8-F-OK	19.06 (0.76)	5.86 (0.15)	20.06 (1.17)	15.62 (0.74)	14.77 (1.12)
BA-S-TK	-15.53 (0.76)	6.36 (0.86)	-10.89 (1.07)	-7.08 (0.84)	-3.50 (1.16)

Appendix D(7): M = 0.5

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	43.73 (3.26)	37.32 (2.18)	38.30 (3.99)	37.12 (3.11)	29.99 (3.75)
Bn-S-GBU	5.18 (1.49)	28.31 (1.42)	1.25 (2.15)+	15.56 (1.64)	9.60 (2.33)
BK-F-PLS	22.56 (1.95)	15.29 (1.63)	81.44 (3.46)	16.92 (1.86)	70.53 (3.25)
BK-S-PFU	-12.44 (1.28)	9.77 (1.33)	-13.78 (1.51)	-3.80 (1.40)	-6.68 (1.63)
BA-F-OK	31.71 (1.62)	19.43 (1.80)	41.39 (2.74)	25.65 (2.56)	32.89 (2.57)
BA-S-OK	-13.87 (1.16)	5.49 (1.34)	-6.78 (1.57)	-5.38 (1.28)	0.90 (1.70)+
BA-F-PLS	28.73 (2.09)	20.96 (1.72)	35.98 (2.55)	22.81 (1.90)	27.81 (2.40)
BA-S-PLS	-18.21 (1.24)	4.58 (1.42)	-13.55 (1.54)	-10.15 (1.37)	-6.42 (1.67)
HD-PT-PLS	26.44 (2.02)	19.46 (1.66)	33.48 (2.48)	7.75 (1.73)	12.07 (2.09)
L1-F-PLS	15.90 (1.83)	8.91 (1.49)	12.26 (1.85)	10.57 (1.75)	8.46 (1.79)
L1-S-PFU	-2.87 (1.18)	21.93 (1.12)	-27.21 (0.80)	6.71 (1.29)	-21.20 (2.73)
S71-S-OK	-11.66 (1.17)	7.21 (1.34)	-4.35 (1.58)	-2.95 (1.29)	3.53 (1.71)
S72-S-OK	-13.23 (1.12)	5.60 (1.27)	-6.22 (1.52)	-4.67 (1.23)	1.51 (1.64)+
S7-S-PFS	-13.46 (1.06)	7.54 (1.16)	-8.66 (1.37)	-4.93 (1.16)	-1.13 (1.48)+
S8-F-OK	7.27 (0.65)	-1.79 (0.08)	5.64 (1.00)	3.85 (0.63)	0.77 (0.95)+
BA-S-TK	-15.23 (0.96)	6.56 (1.10)	-11.05 (1.27)	-6.97 (1.05)	-3.72 (1.38)

Appendix D(8): a_m = 3

Estimation Procedure	E_{MSY}	MSY	Q_{MS}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	48.14 (1.56)	34.05 (0.95)	34.97 (2.58)	41.78 (1.49)	27.07 (2.43)
Bn-S-GBU	11.30 (0.73)	28.31 (0.54)	1.05 (1.63)+	22.68 (0.81)	9.56 (1.77)
BK-F-PLS	17.28 (1.21)	11.33 (1.01)	88.82 (2.55)	12.25 (1.22)	77.78 (2.40)
BK-S-PFU	-13.09 (0.83)	9.41 (0.80)	-15.51 (1.05)	-4.21 (0.91)	-8.39 (1.14)
BA-F-OK	26.42 (1.34)	14.95 (1.09)	36.86 (1.87)	20.99 (1.28)	28.85 (1.76)
BA-S-OK	-10.87 (0.71)	8.42 (0.78)	-1.70 (1.12)+	-1.76 (0.79)	6.58 (1.22)
BA-F-PLS	22.49 (1.35)	16.22 (1.06)	30.51 (1.78)	17.24 (1.30)	22.87 (1.68)
BA-S-PLS	-16.33 (0.79)	8.03 (0.84)	-10.61 (1.11)	-7.78 (0.87)	-3.08 (1.20)
HD-PT-PLS	20.15 (1.36)	14.02 (1.06)	27.86 (1.79)	2.06 (1.15)+	6.84 (1.50)
L1-F-PLS	6.63 (1.24)	1.14 (0.98)+	4.59 (1.32)	2.05 (1.18)+	1.63 (1.27)+
L1-S-PFU	-6.59 (0.78)	17.75 (0.74)	25.01 (0.70)	2.96 (0.85)	-18.68 (0.76)
S71-S-OK	-8.33 (0.74)	9.91 (0.79)	1.07 (1.16)+	1.04 (0.82)+	9.59 (1.25)
S72-S-OK	-10.25 (0.73)	7.91 (0.79)	-1.29 (1.13)+	-1.07 (0.81)+	7.03 (1.22)
S7-S-PFS	-12.80 (0.69)	8.41 (0.72)	-6.83 (1.00)	-3.89 (0.76)	1.02 (0.94)+
S8-F-OK	38.70 (1.00)	11.39 (0.18)	39.33 (1.55)	34.90 (0.97)	33.30 (1.49)
BA-S-TK	-13.62 (0.62)	8.49 (0.68)	-8.51 (0.94)	-4.79 (0.68)	-0.81 (1.02)+

Appendix D(9): a_m = 5

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	44.86 (1.49)	31.68 (0.90)	32.07 (2.50)	38.28 (1.42)	24.03 (2.35)
Bn-S-GBU	9.04 (0.71)	26.19 (0.50)	-0.93 (1.59)+	19.87 (0.77)	7.15 (1.72)
BK-F-PLS	14.77 (1.19)	9.04 (0.94)	83.56 (2.43)	9.55 (1.14)	72.39 (2.28)
BK-S-PFU	-14.89 (0.79)	7.26 (0.74)	-17.50 (1.01)	-6.44 (0.87)	-10.77 (1.09)
BA-F-OK	23.39 (1.23)	12.45 (1.00)	32.76 (1.76)	17.79 (1.18)	24.69 (1.65)
BA-S-OK	-13.01 (0.66)	6.18 (0.72)	-4.66 (1.07)	-4.37 (0.73)	3.11 (1.15)
BA-F-PLS	19.97 (1.27)	13.92 (0.98)	27.43 (1.70)	14.52 (1.21)	19.67 (1.60)
BA-S-PLS	-17.97 (0.75)	6.00 (0.78)	-12.63 (1.06)	-9.83 (0.82)	-5.51 (1.15)
HD-PT-PLS	17.15 (1.22)	11.35 (0.94)	24.24 (1.64)	-0.71 (1.03)+	3.59 (1.37)
L1-F-PLS	4.30 (1.16)	-0.99 (0.90)+	2.22 (1.26)+	-0.44 (1.11)+	-0.96 (1.21)+
L1-S-PFU	-8.53 (0.74)	15.43 (0.69)	-26.35 (0.68)	0.55 (0.81)+	-20.34 (0.74)
S71-S-OK	-10.62 (0.69)	7.53 (0.74)	-2.04 (1.10)+	-1.74 (0.76)	5.95 (1.19)
S72-S-OK	-12.47 (0.68)	5.62 (0.73)	-4.30 (1.07)	-3.78 (0.74)	3.50 (1.16)
S7-S-PFS	-14.66 (0.66)	6.22 (0.68)	-9.22 (0.96)	-6.19 (0.72)	-1.82 (1.04)+
S8-F-OK	21.73 (0.79)	-0.76 (0.08)	17.61 (3.39)	17.92 (1.48)	12.09 (1.11)
BA-S-TK	-15.46 (0.56)	6.43 (0.64)	-10.76 (0.90)	-7.06 (0.64)	-3.49 (0.97)

Appendix D(10): $a_r = 4$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	57.25 (3.21)	47.41 (2.23)	55.76 (4.14)	50.53 (3.15)	46.75 (3.90)
Bn-S-GBU	11.46 (1.52)	34.82 (1.46)	10.09 (2.29)	22.87 (1.67)	19.45 (2.48)
BK-F-PLS	31.61 (2.28)	24.04 (1.90)	100.18 (4.05)	25.98 (2.18)	88.60 (3.81)
BK-S-PFU	-6.79 (1.52)	16.84 (1.58)	-5.88 (1.79)	2.76 (1.67)+	1.12 (1.94)+
BA-F-OK	46.38 (2.58)	31.44 (2.16)	62.97 (3.31)	40.13 (2.47)	53.55 (3.12)
BA-S-OK	-6.53 (1.40)	13.27 (1.61)	4.83 (1.87)	3.04 (1.55)	13.74 (2.03)
BA-F-PLS	36.97 (2.47)	28.94 (2.05)	47.93 (3.03)	31.12 (2.36)	39.37 (2.85)
BA-S-PLS	-14.85 (1.46)	9.06 (1.68)	-8.02 (1.81)	-6.13 (1.61)	-0.20 (1.96)+
HD-PT-PLS	34.31 (2.36)	27.18 (1.98)	44.96 (2.92)	14.89 (2.03)	22.06 (2.48)
L1-F-PLS	24.74 (2.10)	17.46 (1.71)	22.09 (2.13)	19.41 (2.01)	18.37 (2.08)
L1-S-PFU	3.24 (1.40)	29.60 (1.32)	-25.14 (0.89)	13.81 (1.55)	-18.76 (0.97)
S71-S-OK	-3.78 (1.45)	15.67 (1.64)	7.95 (1.94)	6.07 (1.60)	17.13 (2.10)
S72-S-OK	-6.12 (1.29)	13.21 (1.48)	5.01 (1.75)	3.49 (1.42)	13.94 (1.89)
S7-S-PFS	-8.14 (1.23)	14.19 (1.35)	-0.09 (1.61)+	1.26 (1.36)+	8.40 (1.75)
S8-F-OK	-7.98 (0.49)	-8.39 (0.03)	-10.73 (0.80)	-10.59 (0.47)	-14.63 (0.77)
BA-S-TK	-10.21 (1.14)	12.51 (1.30)	-3.46 (1.51)	-1.01 (1.26)+	4.75 (1.64)

Appendix D(11): $\delta = 1.0$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	49.05 (1.55)	34.21 (0.94)	35.61 (2.57)	42.45 (1.48)	27.43 (2.41)
Bn-S-GBU	11.81 (0.74)	28.35 (0.54)	1.44 (1.64)+	23.06 (0.81)	9.77 (1.77)
BK-F-PLS	17.35 (1.26)	11.31 (1.00)	89.42 (2.57)	12.15 (1.20)	77.99 (2.42)
BK-S-PFU	-13.05 (0.83)	9.39 (0.79)	-15.58 (1.05)	-4.31 (0.91)	-8.65 (1.14)
BA-F-OK	27.09 (1.33)	15.10 (1.08)	38.02 (1.88)	21.46 (1.28)	29.69 (1.77)
BA-S-OK	-10.53 (0.72)	8.39 (7.70)+	-1.07 (1.14)+	-1.53 (0.79)+	7.06 (1.23)
BA-F-PLS	22.52 (1.34)	16.15 (1.03)	30.52 (1.79)	17.09 (1.28)	22.64 (1.68)
BA-S-PLS	-16.44 (0.79)	7.80 (0.84)	-10.77 (1.11)	-8.03 (0.86)	-3.44 (1.20)
HD-PT-PLS	19.98 (1.30)	14.35 (1.02)	27.72 (1.74)	2.42 (1.12)	7.20 (1.47)
L1-F-PLS	6.72 (1.23)	1.14 (0.96)+	4.62 (1.31)	1.99 (1.17)+	1.50 (1.27)+
L1-S-PFU	-6.45 (0.77)	17.85 (0.73)	-25.07 (0.70)	2.96 (0.84)	-18.91 (0.75)
S71-S-OK	-7.94 (0.75)	9.95 (0.79)	1.77 (1.17)+	1.32 (0.82)+	10.12 (1.26)
S72-S-OK	-14.31 (0.66)	4.58 (0.71)	-7.74 (1.02)	-5.64 (0.72)	0.05 (1.10)+
S7-S-PFS	-12.74 (0.68)	8.38 (0.70)	-6.76 (1.00)	-3.96 (0.75)	0.89 (1.09)+
S8-F-OK	13.41 (0.08)	-4.20 (0.13)	7.94 (1.15)	10.07 (0.77)	3.18 (1.10)
BA-S-TK	-16.51 (0.57)	5.67 (0.63)	-12.35 (0.86)	-8.07 (0.62)	-4.94 (0.94)

Appendix D(12): δ = 0.25

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	40.88 (1.48)	30.33 (0.87)	28.34 (2.45)	34.70 (1.41)	20.86 (2.31)
Bn-S-GBU	7.04 (0.70)	25.59 (0.49)	-2.84 (1.56)+	17.86 (0.77)	5.37 (1.69)
BK-F-PLS	13.28 (1.19)	7.74 (0.95)	78.52 (2.32)	8.31 (1.14)	68.12 (2.18)
BK-S-PFU	-15.74 (0.77)	6.35 (0.74)	-18.57 (0.98)	-7.21 (0.84)	-11.69 (1.06)
BA-F-OK	20.12 (1.19)	10.57 (0.98)	27.17 (1.66)	14.85 (1.14)	19.76 (1.57)
BA-S-OK	-14.85 (0.64)	5.16 (0.70)	-8.12 (1.00)	-6.24 (0.70)	-0.35 (1.08)+
BA-F-PLS	18.66 (1.26)	12.80 (0.98)	25.43 (1.66)	13.46 (1.20)	18.10 (1.57)
BA-S-PLS	-18.39 (0.73)	5.57 (0.78)	-13.44 (1.03)	-10.14 (0.80)	-6.12 (1.11)
HD-PT-PLS	16.28 (1.23)	11.05 (0.96)	22.81 (1.62)	-0.77 (1.05)+	3.22 (1.37)
L1-F-PLS	2.94 (1.15)	-2.18 (0.90)	0.82 (1.24)+	-1.57 (1.10)+	-2.15 (1.19)+
L1-S-PFU	-9.52 (0.73)	14.31 (0.70)	-26.67 (0.68)	-0.37 (0.81)+	-20.46 (0.74)
S71-S-OK	-12.65 (0.66)	6.21 (0.72)	-5.75 (1.03)	-3.82 (0.73)	2.22 (1.12)+
S72-S-OK	-9.86 (0.72)	7.92 (0.77)	-0.54 (1.15)+	-0.79 (0.80)+	7.62 (1.25)
S7-S-PFS	-15.52 (0.64)	5.38 (0.67)	-10.84 (0.92)	-6.97 (0.71)	-3.30 (1.00)
S8-F-OK	0.67 (0.72)+	-10.13 (0.14)	-6.52 (1.01)	-2.33 (0.70)	-10.83 (0.96)
BA-S-TK	-13.47 (0.61)	8.46 (0.67)	-8.38 (0.94)	-4.77 (0.68)	-0.86 (1.02)+

Appendix D(13): MSY = 200

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	57.44 (1.84)	50.23 (0.90)	44.92 (2.86)	50.71 (1.76)	36.91 (2.70)
Bn-S-GBU	27.85 (0.83)	50.94 (0.47)	17.35 (1.88)	40.94 (0.92)	27.68 (2.04)
BK-F-PLS	17.51 (1.29)	12.00 (1.13)	83.89 (2.89)	12.49 (1.24)	73.72 (2.73)
BK-S-PFU	-8.09 (0.89)	16.20 (1.01)	-13.79 (1.08)	1.32 (0.98)+	-6.20 (1.18)
BA-F-OK	29.64 (1.36)	17.15 (1.18)	40.04 (1.98)	24.10 (1.30)	32.30 (1.87)
BA-S-OK	-3.72 (0.79)	17.24 (0.93)	4.68 (1.25)	6.14 (0.87)	13.89 (1.36)
BA-F-PLS	22.68 (1.40)	16.82 (1.20)	27.40 (1.88)	17.43 (1.34)	20.35 (1.77)
BA-S-PLS	-12.42 (0.95)	13.45 (1.16)	-9.36 (1.29)	-3.45 (1.05)	-1.39 (1.41)+
HD-PT-PLS	20.74 (1.38)	15.25 (1.18)	25.22 (1.85)	2.85 (1.17)	5.27 (1.55)
L1-F-PLS	7.37 (1.15)	2.10 (0.94)	8.36 (1.26)	2.78 (1.10)	5.83 (1.22)
L1-S-PFU	3.74 (0.75)	31.29 (0.84)	-12.70 (0.81)	14.36 (0.82)	-5.01 (0.88)
S71-S-OK	-0.84 (0.83)+	18.84 (0.94)	8.44 (1.33)	9.31 (0.92)	17.98 (1.45)
S72-S-OK	-3.17 (0.80)	16.38 (0.90)	5.23 (1.27)	6.75 (0.88)	14.48 (1.38)
S7-S-PFS	-5.87 (0.72)	17.44 (0.86)	-1.42 (1.06)+	3.77 (0.80)	7.25 (1.16)
S8-F-OK	29.17 (1.07)	7.56 (0.07)	37.52 (2.25)	25.59 (1.03)	31.87 (2.16)
BA-S-TK	-5.76 (0.68)	19.02 (0.85)	-2.40 (1.02)	3.89 (0.75)	6.18 (1.10)

Appendix D(14): MSY = 300

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	33.07 (1.26)	21.11 (0.84)	23.70 (2.28)	27.04 (1.21)	15.82 (2.13)
Bn-S-GBU	-2.90 (0.61)	13.42 (0.51)	-9.99 (1.45)	6.75 (0.67)	-2.95 (1.57)+
BK-F-PLS	14.73 (1.30)	8.60 (0.94)	84.07 (2.23)	9.53 (1.24)	72.34 (2.09)
BK-S-PFU	-17.85 (0.85)	3.09 (0.72)	-17.63 (1.08)	-9.68 (0.94)	-11.19 (1.16)
BA-F-OK	20.22 (1.29)	10.63 (0.98)	29.76 (1.73)	14.77 (1.23)	21.49 (1.62)
BA-S-OK	-17.32 (0.67)	1.30 (0.69)	-8.68 (0.99)	-9.10 (0.74)	-1.54 (1.07)+
BA-F-PLS	19.53 (1.35)	13.09 (0.97)	29.69 (1.74)	14.11 (1.29)	21.43 (1.62)
BA-S-PLS	-20.81 (0.74)	1.99 (0.70)	-13.53 (1.00)	-12.94 (0.81)	-6.77 (1.08)
HD-PT-PLS	17.19 (1.31)	11.06 (0.94)	27.01 (1.68)	-0.57 (1.11)+	5.69 (1.40)
L1-F-PLS	5.37 (1.29)	-0.32 (0.96)+	1.59 (1.32)+	0.59 (1.23)+	-1.70 (1.28)+
L1-S-PFU	-14.02 (0.81)	8.05 (0.69)	-35.10 (0.63)	-5.47 (0.89)	-30.01 (0.68)
S71-S-OK	-15.10 (0.70)	2.64 (0.71)	-6.69 (1.01)	-6.66 (0.77)	0.61 (1.09)+
S72-S-OK	-16.73 (0.67)	1.02 (0.70)+	-8.47 (0.99)	-8.45 (0.74)	-1.30 (1.07)+
S7-S-PFS	-18.19 (0.70)	1.48 (0.66)	-11.29 (0.96)	-10.06 (0.76)	-4.35 (1.04)
S8-F-OK	-11.22 (0.68)	-14.14 (0.33)	-18.41 (0.87)	-13.75 (0.67)	-22.26 (0.83)
BA-S-TK	-19.84 (0.59)	0.71 (0.60)+	-13.44 (0.86)	-11.87 (0.65)	-6.67 (0.93)

Appendix D(15): $B^e_{MSY}/K^e = 0.3$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	7.52 (1.11)	27.87 (0.81)	0.50 (1.90)+	23.43 (1.27)	11.16 (2.10)
Bn-S-GBU	-17.30 (0.54)	24.35 (0.45)	-23.02 (1.21)	9.32 (0.71)	-1.93 (1.55)+
BK-F-PLS	-15.59 (0.82)	4.42 (0.85)	41.01 (1.87)	-3.11 (0.94)	55.97 (2.06)
BK-S-PFU	-36.36 (0.56)	4.43 (0.72)	-36.74 (0.73)	-15.87 (0.74)	-19.41 (0.93)
BA-F-OK	-9.31 (0.85)	7.71 (0.89)	1.21 (1.31)+	4.10 (0.98)	11.95 (1.45)
BA-S-OK	-34.77 (0.49)	3.70 (0.69)	-25.81 (0.83)	-13.76 (0.65)	-5.49 (1.06)
BA-F-PLS	-11.70 (0.87)	9.17 (0.88)	-3.29 (1.23)	1.36 (1.00)+	6.97 (1.36)
BA-S-PLS	-38.49 (0.55)	3.48 (0.80)	-32.47 (0.81)	-18.69 (0.73)	-13.97 (1.03)
HD-PT-PLS	-13.52 (0.86)	7.35 (0.86)	-5.39 (1.20)	-11.48 (0.88)	-6.67 (1.19)
L1-F-PLS	-23.64 (0.78)	-5.63 (0.78)	-22.15 (0.89)	-12.35 (0.89)	-11.10 (1.02)
L1-S-PFU	-31.27 (0.52)	12.92 (0.68)	-41.85 (0.53)	-9.14 (0.69)	-25.91 (0.68)
S71-S-OK	-32.84 (0.52)	5.05 (0.72)	-23.52 (0.87)	-11.21 (0.68)	-2.57 (1.11)
S72-S-OK	-35.96 (0.47)	3.74 (0.65)	-29.59 (0.72)	-15.34 (0.62)	-10.30 (0.91)
S7-S-PFS	-34.27 (0.50)	3.13 (0.70)	-25.37 (0.85)	-13.11 (0.66)	-4.94 (1.08)
S8-F-OK	-18.54 (0.48)	-9.36 (0.07)	-19.40 (0.77)	-4.68 (0.63)	-9.50 (0.87)
BA-S-TK	-36.44 (0.43)	4.21 (0.63)	-30.79 (0.68)	-15.97 (0.56)	-11.84 (0.86)

Appendix D(16): $B^e_{MSY}/K^e = 0.45$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	73.43 (1.86)	36.68 (1.05)	57.51 (3.01)	55.74 (1.67)	40.01 (2.67)
Bn-S-GBU	28.15 (0.87)	29.28 (0.62)	16.03 (1.89)	32.53 (0.90)	18.78 (1.93)
BK-F-PLS	38.62 (1.65)	14.53 (1.16)	116.80 (3.03)	24.48 (1.48)	92.70 (2.69)
BK-S-PFU	1.36 (1.05)	11.07 (0.88)	-2.36 (1.31)	4.83 (1.09)	-0.50 (1.34)
BA-F-OK	49.71 (1.71)	18.37 (1.23)	58.91 (2.26)	34.43 (1.53)	41.25 (2.00)
BA-S-OK	3.67 (0.89)	19.81 (0.85)	11.97 (1.31)	7.21 (0.92)	14.62 (1.34)
BA-F-PLS	44.69 (1.75)	19.47 (1.19)	51.96 (2.22)	29.93 (1.57)	35.07 (1.98)
BA-S-PLS	-2.77 (0.97)	9.27 (0.89)	2.40 (1.32)+	0.55 (1.01)+	4.82 (1.35)
HD-PT-PLS	41.97 (1.70)	17.67 (1.16)	49.00 (2.17)	13.62 (1.36)	18.04 (1.72)
L1-F-PLS	26.64 (1.61)	4.54 (1.12)	21.70 (1.65)	13.72 (1.44)	11.60 (1.51)
L1-S-PFU	8.71 (0.99)	19.08 (0.81)	-15.53 (0.81)	12.43 (1.02)	-13.52 (0.83)
S71-S-OK	6.41 (0.92)	11.25 (0.87)	14.82 (1.33)	10.04 (0.95)	17.54 (1.36)
S72-S-OK	4.32 (0.90)	9.35 (0.86)	12.35 (1.31)	7.89 (0.93)	15.00 (1.34)
S7-S-PFS	1.46 (0.88)	9.84 (0.79)	6.65 (1.22)	4.92 (0.91)	9.17 (1.25)
S8-F-OK	24.76 (0.86)	-5.87 (0.06)	15.22 (1.23)	13.70 (0.78)	3.94 (1.17)
BA-S-TK	0.30 (0.78)+	9.67 (0.74)	4.68 (1.13)	3.72 (0.80)	7.16 (1.16)

Appendix D(17): $N_{1,a} = N_{0,0}\, e^{-aM}\, e^{\epsilon_y}$ $\epsilon_y \sim N(0,\sigma_r^2)$

Estimation Procedure	E_{MSY}	MSY	Q_{MSY}	$E_{0.1}$	$Q_{0.1}$
Bn-F-GBU	44.85 (2.40)	32.62 (1.49)	36.02 (3.12)	38.49 (2.30)	27.93 (2.93)
Bn-S-GBU	8.45 (1.29)	26.64 (1.03)	1.66 (1.92)+	19.41 (1.42)	10.12 (2.08)
BK-F-PLS	18.99 (2.44)	11.89 (1.72)	86.93 (3.57)	13.77 (2.33)	75.81 (3.36)
BK-S-PFU	-10.35 (1.83)	10.38 (1.56)	-12.81 (1.88)	-1.29 (2.01)+	-5.56 (2.04)
BA-F-OK	28.32 (2.43)	16.09 (1.75)	39.80 (2.81)	22.68 (2.32)	31.48 (2.64)
BA-S-OK	-10.88 (1.33)	8.01 (1.25)	-1.34 (1.62)+	-1.87 (1.46)+	6.86 (1.75)
BA-F-PLS	23.90 (2.54)	16.38 (1.79)	30.85 (2.73)	18.46 (2.43)	23.07 (2.57)
BA-S-PLS	-17.38 (1.50)	5.72 (1.48)	-12.43 (1.67)	-9.03 (1.65)	-5.15 (1.81)
HD-PT-PLS	22.32 (2.45)	15.10 (1.71)	28.94 (2.63)	3.94 (2.08)+	7.78 (2.19)
L1-F-PLS	9.66 (2.34)	2.90 (1.65)+	6.09 (1.99)	4.84 (2.23)	2.99 (1.93)+
L1-S-PFU	-2.52 (1.86)+	20.17 (1.51)	-26.57 (0.88)	7.33 (2.05)	-20.45 (0.95)
S71-S-OK	-8.16 (1.35)	9.82 (1.27)	1.69 (1.63)+	1.12 (1.47)+	10.14 (1.76)
S72-S-OK	-10.84 (1.18)	7.01 (1.09)	-1.59 (1.44)+	-1.83 (1.30)+	6.59 (1.56)
S7-S-PFS	-12.07 (1.35)	8.14 (1.19)	-6.23 (1.49)	-3.18 (1.48)	-1.57 (1.59)+
S8-F-OK	6.58 (0.96)	-5.99 (0.05)	2.33 (1.15)	3.48 (0.93)	-2.27 (1.10)
BA-S-TK	-13.40 (1.29)	7.86 (1.18)	-8.95 (1.01)	-4.65 (1.42)	-1.38 (1.52)+

Appendix E: Estimates of the percentage expected discrepancy in the estimates of $Q_{0.1}$ for the estimation procedures listed in Table 9.5. The standard error of the estimated percentage expected discrepancy is given in parenthesis. Column 1 in each Table contains the acronym for the procedure. Columns (1) to (17) below contain the results of the following simulations carried out to test the procedures for robustness:

Column	Alterations made to the age-structured operating model
1	$\sigma_r = 0.13;\ \sigma_q = 0.0$ +
2	$\sigma_r = 0.1;\ \sigma_q = 0.2$
3	$\sigma_r = 0.0;\ \sigma_q = 0.3$ +
4	$\sigma_r = 0.2;\ \sigma_q = 0.2$ +
5	$M = 0.2$ *
6	$M = 0.4$ *
7	$M = 0.5$ *
8	$a_m = 3$
9	$a_m = 5$
10	$a_r = 4$
11	$\delta = 1.0$
12	$\delta = 0.25$
13	$MSY = 200$
14	$MSY = 300$
15	$B^e_{MSY}/K^e = 0.3$
16	$B^e_{MSY}/K^e = 0.45$
17	$N_{1,a} = N_{0,0}\, e^{-aM_e}\, e^{\varepsilon_y} \quad \varepsilon_y \sim N(0;\sigma_r^2)$

Note: * procedures that use a value of M (for these tests only Schnute-85) continue to assume that M = 0.3
+ otherwise the standard specification is the mixed error structure: $\sigma_r = 0.2,\ \sigma_q = 0.1$

Estimation Procedure	1	2	3	4	5	6
Bn-F-GBU	32.15 (1.74)	52.16 (2.24)	58.58 (2.84)	42.11 (2.36)	26.96 (1.60)	38.28 (2.39)
Bn-S-GBU	24.87 (1.21)	28.05 (1.35)	30.97 (1.46)	37.56 (1.73)	18.36 (1.09)	22.59 (1.45)
BK-F-PLS	17.70 (0.83)	75.91 (2.26)	81.29 (2.93)	90.30 (3.81)	79.16 (2.01)	73.72 (2.60)
BK-S-PFU	71.41 (2.06)	19.54 (0.79)	17.92 (0.86)	47.18 (14.21)	14.47 (0.66)	18.33 (0.87)
BA-F-OK	22.63 (0.88)	29.66 (1.52)	39.46 (2.55)	33.73 (1.98)	24.96 (1.23)	34.18 (1.85)
BA-S-OK	9.87 (0.56)	13.39 (0.72)	21.36 (1.38)	20.23 (1.19)	13.76 (0.76)	16.35 (0.96)
BA-F-PLS	23.35 (1.31)	25.85 (1.38)	31.66 (1.75)	44.15 (3.10)	22.37 (1.16)	17.49 (0.89)
BA-S-PLS	16.31 (0.79)	14.75 (0.76)	17.19 (0.94)	28.37 (1.86)	12.88 (0.66)	30.14 (1.65)
HD-PT-PLS	16.27 (0.97)	17.58 (0.99)	22.11 (1.32)	32.72 (2.45)	14.64 (0.81)	21.36 (1.22)
L1-F-PLS	14.72 (0.80)	15.34 (0.79)	18.94 (1.10)	26.81 (1.92)	13.50 (0.64)	18.21 (0.99)
L1-S-PFU	22.13 (0.76)	20.33 (0.67)	18.92 (0.66)	31.86 (1.11)	17.59 (0.65)	22.10 (0.69)
S71-S-OK	11.00 (0.59)	15.64 (0.87)	22.56 (1.39)	22.85 (1.32)	16.20 (0.85)	17.09 (0.98)
S72-S-OK	10.08 (0.57)	14.60 (0.83)	20.92 (1.19)	20.32 (1.16)	14.21 (0.78)	16.12 (0.95)
S7-S-PFS	12.58 (0.66)	12.63 (0.69)	16.71 (0.96)	22.95 (1.55)	11.22 (0.61)	14.81 (0.82)
S8-F-OK	25.63 (0.00)	32.11 (0.62)	23.79 (1.58)	16.72 (0.62)	14.84 (0.84)	17.54 (0.94)
BA-S-TK	12.64 (0.61)	12.10 (0.65)	14.98 (0.88)	20.71 (1.22)	10.58 (0.57)	14.33 (0.76)

Estimation Procedure	7	8	9	10	11	12
Bn-F-GBU	45.19 (3.08)	33.48 (2.08)	31.12 (1.99)	57.41 (3.27)	29.26 (1.90)	33.30 (2.09)
Bn-S-GBU	25.97 (1.76)	20.79 (1.32)	19.97 (1.25)	30.77 (1.97)	19.67 (1.19)	20.69 (1.34)
BK-F-PLS	73.08 (3.02)	78.37 (2.33)	73.02 (2.20)	91.93 (3.48)	68.78 (2.10)	78.58 (2.34)
BK-S-PFU	20.72 (1.05)	15.99 (0.75)	16.52 (0.75)	22.76 (1.31)	16.74 (0.74)	16.07 (0.75)
BA-F-OK	38.95 (2.21)	31.40 (1.58)	27.66 (1.45)	57.40 (2.83)	23.69 (1.32)	32.06 (1.59)
BA-S-OK	19.18 (1.18)	15.12 (0.86)	13.66 (0.79)	25.68 (1.50)	12.73 (0.72)	15.35 (0.87)
BA-F-PLS	35.21 (1.97)	26.99 (1.42)	24.35 (1.32)	46.03 (2.42)	23.20 (1.27)	26.80 (1.41)
BA-S-PLS	20.72 (1.11)	14.82 (0.77)	14.83 (0.75)	22.59 (1.34)	14.65 (0.72)	14.97 (0.77)
HD-PT-PLS	25.85 (1.51)	18.20 (1.05)	16.67 (0.90)	32.87 (1.93)	16.46 (0.91)	18.10 (1.02)
L1-F-PLS	21.89 (1.25)	15.59 (0.81)	15.04 (0.75)	26.89 (1.66)	14.99 (0.74)	15.49 (0.80)
L1-S-PFU	22.45 (0.72)	19.55 (0.66)	20.92 (0.67)	21.26 (0.73)	21.01 (0.67)	19.70 (0.67)
S71-S-OK	19.71 (1.19)	16.64 (0.91)	14.72 (0.83)	27.47 (1.60)	13.31 (0.75)	16.93 (0.93)
S72-S-OK	18.76 (1.14)	15.22 (0.87)	13.86 (0.79)	24.36 (1.41)	13.12 (0.73)	15.86 (0.88)
S7-S-PFS	17.53 (0.99)	12.90 (0.71)	12.52 (0.68)	20.94 (1.26)	12.33 (0.65)	12.91 (0.72)
S8-F-OK	11.57 (0.61)	33.98 (1.42)	15.69 (0.91)	16.66 (0.58)	12.70 (0.78)	15.39 (0.67)
BA-S-TL	16.79 (0.91)	12.21 (0.66)	12.13 (0.63)	19.36 (1.13)	12.18 (0.61)	12.25 (0.66)

Estimation Procedure	13	14	15	16	17
Bn-F-GBU	39.95 (2.52)	20.48 (1.66)	24.54 (1.57)	43.33 (2.46)	39.08 (2.37)
Bn-S-GBU	30.08 (1.90)	19.78 (0.96)	18.77 (0.99)	25.34 (1.60)	24.53 (1.53)
BK-F-PLS	74.92 (2.60)	72.71 (2.03)	57.10 (1.94)	93.16 (2.63)	77.54 (3.20)
BK-S-PFU	15.45 (0.76)	17.64 (0.77)	21.04 (0.77)	16.42 (0.85)	22.74 (1.49)
BA-F-OK	34.68 (1.69)	25.24 (1.39)	18.76 (1.12)	42.34 (1.91)	36.29 (2.38)
BA-S-OK	19.41 (1.05)	13.19 (0.67)	26.65 (0.72)	19.38 (1.07)	19.46 (1.32)
BA-F-PLS	26.70 (1.40)	25.16 (1.39)	16.76 (0.96)	37.33 (1.80)	31.75 (2.17)
BA-S-PLS	17.16 (0.90)	14.65 (0.70)	17.95 (0.75)	16.51 (0.91)	21.27 (1.25)
HD-PT-PLS	19.06 (1.03)	16.85 (0.97)	15.74 (0.75)	24.20 (1.39)	23.51 (1.69)
L1-F-PLS	14.86 (0.86)	15.97 (0.79)	16.42 (0.67)	19.46 (1.13)	21.51 (1.11)
L1-S-PFU	14.86 (0.86)	30.14 (0.65)	25.95 (0.67)	16.03 (0.62)	21.96 (0.81)
S71-S-OK	22.66 (1.16)	13.37 (0.68)	13.50 (0.73)	21.51 (1.11)	21.01 (1.32)
S72-S-OK	19.81 (1.09)	13.33 (0.66)	13.60 (0.72)	19.64 (1.07)	18.89 (1.09)
S7-S-PFS	14.95 (0.81)	13.17 (0.67)	14.46 (0.65)	16.07 (0.93)	18.22 (1.13)
S8-F-OK	33.03 (2.09)	22.86 (0.76)	13.77 (0.60)	13.32 (0.85)	13.20 (0.72)
BA-S-TK	14.10 (0.76)	13.06 (0.60)	15.14 (0.62)	14.55 (0.83)	16.71 (1.09)

Appendix F: Estimates of the percentage bias in the estimates of the variance of the target effort level $E_{0.1}$ used in the management of the ICSEAF hake stocks for different variance estimation procedures. Standard errors of these bias estimates are given in parenthesis. The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A. All artificial data sets are generated using σ_q = 0.13 and σ_r = 0. Tables (1) to (4) contain the results of the following simulations :

Table	Quantity Estimated
1	S.e. of $\hat{E}_{0.1}$
2	C.v. of $\hat{E}_{0.1}$
3	Lower 95% C.I. limit
4	Upper 95% C.I. limit

Appendix F(1): S.e. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	10.15 (2.19)	84.84 (7.36)	64.10 (2.36)
Infinitesimal Jack-knife	87.50 (3.49)	*	36.94 (1.66)
"Naive" Bootstrap	54.44 (4.15)	*	97.96 (5.86)
Permuted "Naive" Bootstrap	70.61 (11.45)	*	103.26 (8.86)
Punt No 1 Bootstrap	-22.99 (1.46)	90.08 (19.45)	-34.77 (0.93)
Punt No 2 Bootstrap	-58.56 (0.75)	-18.15 (2.79)	-69.16 (0.41)
Punt-DSB Bootstrap	-17.16 (2.33)	*	-9.17 (5.06)+
(Conditioned) Residual Bootstrap	-10.05 (1.69)	-15.79 (1.93)	-46.07 (1.34)
(Conditioned) Parametric Bootstrap	-2.47 (1.89)+	0.34 (2.26)+	-41.87 (1.45)
Information Matrix	??	144.13 (10.25)	*

Appendix F(2): C.v. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure: Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	9.39 (1.84)	181.43 (56.90)	63.64 (1.90)
Infinitesimal Jack-knife	86.23 (2.87)	*	36.59 (1.20)
"Naive" Bootstrap	53.61 (3.82)	*	98.86 (5.83)
Permuted "Naive" Bootstrap	69.71 (11.23)	*	104.42 (9.06)
Punt No 1 Bootstrap	-23.31 (1.27)	92.20 (23.62)	-34.94 (0.72)
Punt No 2 Bootstrap	-58.72 (0.65)	-19.69 (2.16)	-69.25 (0.30)
Punt-DSB Bootstrap	-17.13 (2.31)	*	-8.87 (5.38)+
(Conditioned) Residual Bootstrap	-10.32 (1.51)	-14.54 (1.48)	-46.14 (1.23)
(Conditioned) Parametric Bootstrap	-3.40 (1.47)	7.94 (5.85)+	-41.96 (1.25))
Information Matrix	??	139.16 (5.52)	*

Appendix F(3): Lower 95% C.I. limit

Variance Estimation Procedure	Model Estimation Procedure: Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-0.92 (0.61)+	-416.75 (48.68)	-21.87 (0.71)
Infinitesimal Jack-knife	-18.25 (0.67)	*	-14.68 (0.64)
"Naive" Bootstrap	-13.19 (1.00)	*	-33.17 (1.80)
Permuted "Naive" Bootstrap	-21.45 (2.88)	*	-31.31 (2.76)
Punt No 1 Bootstrap	5.12 (0.67)	-120.73 (-19.38)	5.76 (0.80)
Punt No 2 Bootstrap	13.53 (0.69)	-11.35 (2.18)	15.85 (0.87)
Punt-DSB Bootstrap	3.74 (0.85)	*	-1.75 (1.79)+
(Conditioned) Residual Bootstrap	2.06 (0.68)	-13.74 (2.32)	14.14 (9.28)+
(Conditioned) Parametric Bootstrap	0.36 (0.65)+	35.95 (1.98)	13.54 (0.90)
(Conditioned) Parametric Bootstrap (BC)	1.11 (0.65)+	5.36 (3.39)+	-6.43 (1.99)
Information Matrix	??	-853.52 (55.46)	21.58 (0.85)

Appendix F(4): Upper 95% C.I. limit

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-0.40 (0.72)+	30.44 (3.70)	9.66 (0.88)
Infinitesimal Jack-knife	11.23 (0.90)	444.75 (81.60)	4.88 (0.80)
"Naive" Bootstrap	8.28 (0.97)	*	15.84 (1.33)
Permuted "Naive" Bootstrap	9.18 (2.07)	*	19.49 (1.84)
Punt No 1 Bootstrap	-4.12 (0.66)	25.29 (7.05)	-8.81 (0.72)
Punt No 2 Bootstrap	-9.82 (0.59)	-12.42 (1.96)	-15.20 (0.65)
Punt-DSB Bootstrap	-3.19 (0.70)	*	-4.05 (1.23)
(Conditioned) Residual Bootstrap	-2.05 (0.69)	-11.59 (1.67)	-10.91 (0.73)
(Conditioned) Parametric Bootstrap	0.47 (0.87)+	13.44 (1.94)	-6.30 (0.81)
(Conditioned) Parametric Bootstrap (BC)	0.64 (0.93)+	-14.81 (2.73)	-12.26 (0.92)
Information Matrix	??	54.11 (5.29)	-19.21 (0.57)

Appendix G: As for Appendix F, except that all artificial data sets are generated using σ_q = 0.1 and σ_r = 0.2. Tables (1) to (4) contain the results of the following simulations :

Table	Quantity Estimated
1	S.e. of $\hat{E}_{0.1}$
2	C.v. of $\hat{E}_{0.1}$
3	Lower 95% C.I. limit
4	Upper 95% C.I. limit

Appendix G(1): S.e. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-42.68 (1.84)	58.98 (5.60)	-57.27 (2.42)
Infinitesimal Jack-knife	34.13 (4.08)	624.66 (99.86)	99.52 (1.78)
"Naive" Bootstrap	-15.19 (4.44)	*	-50.57 (2.75)
Permuted "Naive" Bootstrap	-2.89 (4.54)+	*	-59.74 (0.90)
Punt No 1 Bootstrap	-56.61 (1.65)	329.90 (208.63)+	*
Punt No 2 Bootstrap	-77.32 (0.88)	-94.32 (0.27)	*
Punt-DSB Bootstrap	-53.77 (2.17)	*	*
(Conditioned) Residual Bootstrap	-50.87 (1.66)	-29.71 (2.32)	-61.92 (2.90)
(Conditioned) Parametric Bootstrap	-44.32 (2.65)	-14.26 (2.70)	-52.22 (2.78)
Information Matrix	??	120.41 (8.81)	*

Appendix G(2): C.v. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-44.13 (1.34)	78.83 (19.62)	-57.22 (0.89)
Infinitesimal Jack-knife	2.05 (2.30)+	855.99 (197.41)	*
"Naive" Bootstrap	-17.52 (3.45)	*	-49.30 (3.39)
Permuted "Naive" Bootstrap	-5.51 (3.67)+	*	-60.27 (0.98)
Punt No 1 Bootstrap	-57.05 (1.71)	309.65 (209.78)+	*
Punt No 2 Bootstrap	-77.47 (0.99)	-94.53 (0.17)	*
Punt-DSB Bootstrap	-53.83 (2.16)	511.01 (393.61)+	*
(Conditioned) Residual Bootstrap	-50.94 (1.82)	-28.41 (1.90)	-61.54 (3.05)
(Conditioned) Parametric Bootstrap	-46.52 (1.82)	-10.57 (3.05)	-52.63 (2.81)
Information Matrix	??	114.54 (4.55)	*

Appendix G(3): Lower 95% C.I. limits

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	16.07 (1.07)	-129.90 (6.16)	26.79 (1.38)
Infinitesimal Jack-knife	-3.53 (1.10)	*	*
"Naive" Bootstrap	0.09 (1.81)+	*	13.74 (1.71)
Permuted "Naive" Bootstrap	-6.70 (1.60)	*	20.93 (1.50)
Punt No 1 Bootstrap	19.02 (1.27)	-594.04 (-38.13)	-517.44 (29.39)
Punt No 2 Bootstrap	28.48 (1.34)	108.34 (5.00)	-650.45 (95.72)
Punt-DSB Bootstrap	17.72 (1.48)	*	-560.31 (63.11)
(Conditioned) Residual Bootstrap	16.39 (1.32)	6.56 (3.70)+	18.31 (1.67)
(Conditioned) Parametric Bootstrap	13.61 (1.50)	46.21 (2.84)	20.21 (2.37)
(Conditioned) Parametric Bootstrap (BC)	16.01 (1.29)	11.56 (4.03)	4.80 (3.52)+
Information Matrix	??	-216.70 (9.20)	47.05 (1.53)

Appendix G(4): Upper 95% C.I. limits

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-10.36 (1.14)	12.95 (1.07)	-13.39 (0.94)
Infinitesimal Jack-knife	-2.05 (1.38)+	316.23 (55.15)	*
"Naive" Bootstrap	-6.35 (1.61)	*	-12.52 (0.97)
Permuted "Naive" Bootstrap	-3.01 (1.51)	*	-12.45 (1.01)
Punt No 1 Bootstrap	-16.33 (1.04)	107.30 (44.94)	290.18 (16.54)
Punt No 2 Bootstrap	-21.32 (0.90)	-49.34 (1.35)	365.99 (54.47)
Punt-DSB Bootstrap	-15.65 (1.06)	*	314.62 (36.11)
(Conditioned) Residual Bootstrap	-14.95 (1.03)	-22.54 (1.87)	-15.12 (1.04)
(Conditioned) Parametric Bootstrap	-15.04 (1.06)	3.37 (2.39)+	-14.44 (1.03)
(Conditioned) Parametric Bootstrap (BC)	-13.64 (2.05)	-23.35 (2.66)	-17.34 (1.21)
Information Matrix	??	36.32 (4.40)	-23.87 (0.79)

Appendix H: As for Appendix F, except that all artificial data sets are generated using σ_q = 0 and σ_r = 0.3. Tables (1) to (4) contain the results of the following simulations:

Table	Quantity Estimated
1	S.e. of $\hat{E}_{0.1}$
2	C.v. of $\hat{E}_{0.1}$
3	Lower 95% C.I. limit
4	Upper 95% C.I. limit

Appendix H(1): S.e. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-77.27 (1.68)	-47.13 (2.46)	-24.92 (9.24)
Infinitesimal Jack-knife	-60.17 (2.94)	331.57 (86.27)	-55.11 (1.22)
"Naive" Bootstrap	??	*	-36.25 (3.56)
Permuted "Naive" Bootstrap	-59.54 (2.57)	290.75 (179.90)+	12.36 (6.87)+
Punt No 1 Bootstrap	??	-57.98 (15.15)	-77.10 (1.51)
Punt No 2 Bootstrap	-98.99 (0.22)	-84.85 (0.68)	-89.97 (0.66)
Punt-DSB Bootstrap	??	*	-75.33 (1.83)
(Conditioned) Residual Bootstrap	??	-80.17 (0.91)	-84.65 (1.68)
(Conditioned) Parametric Bootstrap	-74.77 (2.14)	-63.07 (1.74)	-75.63 (2.81)
Information Matrix	??	-10.55 (9.14)+	*

Appendix H(2): C.v. of $\hat{E}_{0.1}$

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-77.52 (1.85)	-41.12 (3.81)	-39.06 (9.49)
Infinitesimal Jack-knife	-60.91 (2.97)	220.94 (59.50)	-57.61 (0.86)
"Naive" Bootstrap	??	-32.09 (11.63)	-44.33 (3.68)
Permuted "Naive" Bootstrap	-59.13 (3.39)	*	11.21 (7.55)+
Punt No 1 Bootstrap	??	-74.09 (3.39)	-81.29 (2.03)
Punt No 2 Bootstrap	-96.41 (0.38)	-83.98 (0.66)	-91.85 (0.99)
Punt-DSB Bootstrap	??	289.01 (276.39)+	-75.58 (2.32)
(Conditioned) Residual Bootstrap	??	-76.03 (1.57)	-89.14 (1.89)
(Conditioned) Parametric Bootstrap	-61.47 (13.73)	-51.82 (4.63)	-82.64 (3.09)
Information Matrix	??	-19.58 (3.14)	*

Appendix H(3): Lower 95% C.I. limit

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	52.89 (2.35)	78.21 (10.25)	-6.02 (10.55)+
Infinitesimal Jack-knife	37.32 (2.47)	*	25.51 (2.74)
"Naive" Bootstrap	??	*	-8.83 (6.48)+
Permuted "Naive" Bootstrap	22.56 (1.89)	-733.02 (308.98)	-26.93 (4.97)
Punt No 1 Bootstrap	??	63.13 (36.63)+	45.87 (4.99)
Punt No 2 Bootstrap	*	105.29 (9.98)	63.10 (4.43)
Punt-DSB Bootstrap	??	*	43.50 (5.11)
(Conditioned) Residual Bootstrap	??	88.75 (10.61)	55.98 (5.12)
(Conditioned) Parametric Bootstrap	113.37 (3.99)	231.22 (11.16)	46.98 (5.82)
(Conditioned) Parametric Bootstrap (BC)	115.25 (4.05)	174.33 (11.14)	39.39 (7.03)
Information Matrix	??	-98.34 (2.32)	72.38 (3.36)

Appendix H(4): Upper 95% C.I. limit

Variance Estimation Procedure	Model Estimation Procedure		
	Butterworth-Andrew (BA-F-OK)	Lleonart *et al.* (Ll-F-PEU)	Babayan *et al.* (Bn-F-GLU)
Jack-knife	-28.02 (1.50)	-34.76 (2.30)	-13.52 (3.40)
Infinitesimal Jack-knife	-22.25 (1.87)	132.88 (39.10)	-24.39 (1.47)
"Naive" Bootstrap	??	*	-5.99 (2.29)
Permuted "Naive" Bootstrap	-21.25 (1.39)	100.19 (50.97)	3.14 (2.39)+
Punt No 1 Bootstrap	??	51.78 (34.07)+	-25.63 (1.62)
Punt No 2 Bootstrap	-85.55 (2.20)	-52.53 (1.99)	-31.81 (1.56)
Punt-DSB Bootstrap	??	*	-24.78 (1.73)
(Conditioned) Residual Bootstrap	??	-50.02 (1.97)	-29.26 (1.73)
(Conditioned) Parametric Bootstrap	-29.16 (1.82)	-33.95 (2.09)	-30.00 (1.34)
(Conditioned) Parametric Bootstrap (BC)	-27.66 (2.33)	-46.07 (1.73)	-33.68 (1.90)
Information Matrix	??	-18.57 (5.19)	-40.55 (1.16)

Appendix I: Estimates of the percentage bias and expected discrepancy in the estimates of the variance of selected variables used in the management of the ICSEAF hake stocks for different variance estimation procedures. Standard errors of these estimates are given in parenthesis. The Butterworth age-structured operating model used to generate the artificial data is described in Appendix 7.A. All artificial data sets are generated using σ_q = 0.13 and σ_r = 0. Tables (1) to (6) contain the results of the following simulations:

Table	Quantity Estimated
1	S.e. of $\hat{E}_{0.1}$
2	C.v. of $\hat{E}_{0.1}$
3	Lower 95% C.I. limit for $\hat{E}_{0.1}$
4	Upper 95% C.I. limit for $\hat{E}_{0.1}$
5	S.e. of $\hat{Q}_{0.1}$
6	C.v. of $\hat{Q}_{0.1}$

Appendix I(1): S.e. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	11.74 (1.96)	0.89 (1.88)+	-7.16 (1.69)
L1-F-PLS	-18.02 (1.82)	-35.73 (1.77)	-12.42 (2.59)
S71-S-OK	14.25 (2.03)	-3.87 (1.72)	-3.68 (1.71)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	23.72 (1.46)	22.68 (1.21)	21.99 (1.06)
L1-F-PLS	28.25 (1.19)	41.24 (1.20)	35.31 (1.53)
S71-S-OK	25.29 (1.53)	21.53 (1.07)	21.40 (1.07)

Appendix I(2): C.v. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	11.46 (1.77)	0.47 (1.67)+	-6.77 (1.72)
L1-F-PLS	-17.82 (1.55)	-37.22 (1.22)	-14.57 (1.88)
S71-S-OK	13.66 (1.78)	-4.28 (1.49)	-3.30 (1.74)+

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	22.28 (1.30)	20.53 (1.03)	22.31 (1.07)
L1-F-PLS	25.64 (1.02)	38.86 (0.99)	27.83 (1.13)
S71-S-OK	23.20 (1.32)	19.00 (0.91)	21.63 (1.09)

Appendix I(3): Lower 95% C.I. limit for $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	-0.92 (0.55)+	-0.60 (0.60)+	2.38 (0.67)
L1-F-PLS	6.08 (1.33)	11.95 (1.89)	1.95 (1.17)
S71-S-OK	0.09 (0.54)+	-2.95 (1.36)	2.76 (0.70)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	6.81 (0.34)	7.30 (0.38)	8.56 (0.43)
L1-F-PLS	16.82 (0.89)	25.10 (1.26)	14.40 (0.74)
S71-S-OK	6.97 (0.33)	12.02 (1.15)	9.06 (0.44)

Appendix I(4): Upper 95% C.I. for $\bar{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	0.97 (0.58)+	-1.36 (0.70)+	-1.26 (0.53)
L1-F-PLS	-5.51 (1.07)	-22.08 (1.05)	-7.68 (1.33)
S71-S-OK	1.82 (0.62)	-1.77 (0.71)	-1.10 (0.55)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	6.75 (0.40)	8.43 (0.45)	6.61 (0.34)
L1-F-PLS	14.16 (0.68)	24.33 (0.83)	18.51 (0.80)
S71-S-OK	7.46 (0.42)	8.76 (0.45)	6.88 (0.34)

Appendix I(5): S.e. of $\bar{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	6.31 (1.79)	0.52 (1.47)+	-2.66 (1.31)
L1-F-PLS	-31.91 (1.56)	-36.90 (1.50)	-19.96 (1.55)
S71-S-OK	-1.31 (1.59)+	-2.92 (1.41)	3.86 (1.47)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	22.94 (1.12)	18.34 (0.91)	16.71 (0.79)
L1-F-PLS	36.07 (1.14)	40.31 (1.09)	27.52 (0.97)
S71-S-OK	19.60 (0.99)	17.79 (0.86)	18.18 (0.92)

Appendix I(6): C.v. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	7.23 (1.84)	1.18 (1.43)+	-0.75 (1.63)+
Ll-F-PLS	-31.59 (1.28)	-37.46 (1.06)	-19.19 (1.26)
S71-S-OK	-0.53 (1.60)+	-2.25 (1.36)+	2.29 (1.77)+

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	23.24 (1.19)	17.90 (0.87)	20.44 (0.99)
Ll-F-PLS	33.86 (1.02)	38.14 (0.96)	24.02 (0.87)
S71-S-OK	19.64 (1.01)	17.34 (0.82)	21.68 (1.13)

Appendix J: As for Appendix I except that all artificial data sets are generated using σ_q = 0.1 and σ_r = 0.2. Tables (1) to (6) contain the results of the following simulations:

Table	Quantity Estimated
1	S.e. of $\hat{E}_{0.1}$
2	C.v. of $\hat{E}_{0.1}$
3	Lower 95% C.I. limit for $\hat{E}_{0.1}$
4	Upper 95% C.I. limit for $\hat{E}_{0.1}$
5	S.e. of $\hat{Q}_{0.1}$
6	C.v. of $\hat{Q}_{0.1}$

Appendix J(1): S.e. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-34.88 (1.85)	-38.66 (2.73)	-44.13 (1.67)
L1-F-PLS	-27.45 (2.06)	-52.62 (1.78)	-36.47 (2.57)
S71-S-OK	-32.00 (1.96)	-43.34 (2.02)	-43.17 (1.40)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	40.61 (1.30)	48.80 (1.97)	47.66 (1.22)
L1-F-PLS	37.27 (1.30)	56.70 (1.17)	48.57 (1.57)
S71-S-OK	38.60 (1.40)	49.13 (1.39)	45.13 (1.12)

Appendix J(2): C.v. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-35.38 (1.58)	-39.18 (2.33)	-42.70 (2.30)
L1-F-PLS	-27.40 (1.84)	-54.57 (1.11)	-39.03 (1.66)
S71-S-OK	-32.72 (1.64)	-43.65 (1.73)	-42.11 (1.72)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	39.28 (1.15)	47.69 (1.57)	49.18 (1.70)
L1-F-PLS	34.37 (1.28)	54.87 (1.05)	43.37 (1.15)
S71-S-OK	37.16 (1.20)	48.08 (1.17)	46.20 (1.23)

Appendix J(3): Lower 95% C.I. limit for $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	10.91 (0.91)	13.87 (1.27)	16.16 (1.21)
L1-F-PLS	5.87 (1.53)	20.67 (2.25)	11.48 (1.44)
S71-S-OK	9.42 (0.90)	12.18 (1.77)	17.34 (1.19)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	14.84 (0.65)	20.34 (0.84)	21.05 (0.86)
L1-F-PLS	19.22 (0.99)	31.83 (1.64)	20.01 (1.00)
S71-S-OK	13.98 (0.62)	24.52 (1.14)	21.77 (0.84)

Appendix J(4): Upper 95% C.I. limit for $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure: Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	-8.01 (0.86)	-9.08 (1.39)	-11.38 (0.73)
L1-F-PLS	-11.05 (1.13)	-32.05 (1.15)	-16.15 (1.51)
S71-S-OK	-7.61 (0.89)	-10.16 (1.21)	-11.11 (0.74)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure: Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	12.81 (0.58)	17.10 (1.04)	14.09 (0.51)
L1-F-PLS	17.93 (0.69)	33.97 (0.90)	24.93 (0.91)
S71-S-OK	12.96 (0.59)	16.69 (0.87)	13.74 (0.53)

Appendix J(5): S.e. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure: Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-32.88 (1.64)	-31.94 (2.53)	-38.41 (1.35)
L1-F-PLS	-29.73 (2.19)	-41.66 (2.16)	-27.10 (2.38)
S71-S-OK	-36.39 (1.64)	-36.72 (1.95)	-38,78 (1.21)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure: Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	37.42 (1.19)	41.92 (1.85)	40.83 (1.03)
L1-F-PLS	40.20 (1.36)	49.55 (1.33)	39.66 (1.51)
S71-S-OK	40.15 (1.24)	42.91 (1.35)	40.21 (1.01)

Appendix J(6): C.v. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-35.93 (1.40)	-35.22 (1.98)	-39.07 (1.71)
L1-F-PLS	-30.86 (1.78)	-44.89 (1.38)	-28.60 (1.56)
S71-S-OK	-40.91 (1.37)	-41.26 (1.53)	-41.24 (1.41)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	37.71 (1.19)	42.08 (1.33)	43.22 (1.24)
L1-F-PLS	36.64 (1.26)	46.50 (1.15)	33.99 (1.05)
S71-S-OK	42.27 (1.20)	44.53 (1.10)	43.74 (1.07)

Appendix K: As for Appendix I except that all artificial data sets are generated using σ_q = 0 and σ_r = 0.3. Tables (1) to (6) contain the results of the following simulations:

Table	Quantity Estimated
1	S.e. of $\hat{E}_{0.1}$
2	C.v. of $\hat{E}_{0.1}$
3	Lower 95% C.I. limit for $\hat{E}_{0.1}$
4	Upper 95% C.I. limit for $\hat{E}_{0.1}$
5	S.e. of $\hat{Q}_{0.1}$
6	C.v. of $\hat{Q}_{0.1}$

Appendix K(1): S.e. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-72.67 (1.89)	-73.01 (2.09)	-56.85 (10.48)
L1-F-PLS	-57.93 (1.66)	-71.60 (1.21)	-76.36 (1.07)
S71-S-OK	-73.05 (1.61)	??	-78.59 (1.41)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	75.99 (1.26)	77.59 (1.26)	117.56 (8.21)
L1-F-PLS	60.63 (1.21)	72.10 (1.08)	76.67 (0.98)
S71-S-OK	75.28 (1.13)	??	80.38 (0.92)

Appendix K(2): C.v. of $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-71.95 (2.28)	-65.22 (5.65)	*
L1-F-PLS	-56.27 (2.19)	-72.22 (0.99)	-76.84 (0.90)
S71-S-OK	-33.46 (1.34)	??	-76.69 (2.08)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	76.40 (1.59)	82.47 (4.65)	*
L1-F-PLS	61.50 (1.53)	72.46 (0.91)	77.37 (0.70)
S71-S-OK	74.24 (1.15)	??	81.58 (1.11)

Appendix K(3): Lower 95% C.I. limit for $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	46.09 (1.92)	129.48 (3.92)	*
L1-F-PLS	33.44 (2.56)	36.08 (2.76)	34.62 (2.01)
S71-S-OK	46.42 (1.76)	??	51.34 (2.15)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	49.80 (1.50)	136.35 (2.84)	*
L1-F-PLS	41.99 (1.99)	47.99 (1.89)	38.16 (1.73)
S71-S-OK	49.18 (1.43)	??	55.93 (1.63)

Appendix K(4): Upper 95% C.I. limit for $\hat{E}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	-20.70 (1.28)	-18.20 (2.11)	-57.99 (6.96)
L1-F-PLS	-22.42 (1.25)	-37.28 (1.25)	-33.43 (1.19)
S71-S-OK	-22.91 (1.20)	??	-21.45 (1.29)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap BC	(Conditioned) Residual Bootstrap
BA-S-OK	24.94 (0.92)	27.30 (1.67)	94.57 (5.10)
L1-F-PLS	26.36 (0.89)	39.31 (0.97)	35.86 (0.86)
S71-S-OK	26.48 (0.86)	??	25.37 (0.96)

Appendix K(5): S.e. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-72.92 (1.69)	-70.58 (2.22)	-58.13 (10.04)
L1-F-PLS	-53.01 (2.05)	-61.16 (1.84)	-67.30 (1.44)
S71-S-OK	-75.22 (1.42)	??	-78.62 (1.33)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	75.33 (1.16)	75.92 (1.33)	115.90 (7.78)
L1-F-PLS	57.78 (1.44)	64.47 (1.32)	69.06 (1.05)
S71-S-OK	76.77 (1.04)	??	80.12 (0.90)

Appendix K(6): C.v. of $\hat{Q}_{0.1}$

(Percentage bias)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	-74.98 (1.51)	-66.16 (5.05)	*
L1-F-PLS	-54.63 (2.23)	-64.37 (1.33)	-69.06 (1.07)
S71-S-OK	-78.16 (0.97)	??	-79.16 (1.55)

(Percentage expected discrepancy)

Model Estimation Procedure	Variance Estimation Procedure		
	Jack-knife	(Conditioned) Parametric Bootstrap	(Conditioned) Residual Bootstrap
BA-S-OK	76.99 (1.03)	80.67 (4.12)	*
L1-F-PLS	60.19 (1.56)	65.36 (1.12)	69.82 (0.85)
S71-S-OK	78.21 (0.95)	??	82.11 (0.70)